A HIGHWAY SAFETY EXPERT SYSTEM: A NEW APPROACH

TO SAFETY PROGRAMS

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We accept this thesis as conforming
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The University of British Columbia
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Date April 24th, 1985
This thesis describes the development of a highway safety expert system. The objective of the system is to provide highway safety officials with an efficient and reliable tool to identify accident prone locations and then quickly and reliably advise on the appropriate countermeasure(s) based on an analysis of the accident and roadway environment data. The main advantage of the system is its ability to process a large amount of accident data, separating locations which are most promising to be treated by engineering measures and providing advice on the countermeasures and their expected effectiveness. The system also provides an enhancement to many of the techniques currently used in highway safety improvement programs including two new methods for identifying accident prone locations. The nature of traffic safety problems which are ill-structured, poorly understood, and lack explicit algorithms makes it well suited to the expert system approach. The system consists of three basic phases: Detection; Diagnosis; and Remedy. The three phases comprise the main components of highway safety improvement projects. This thesis describes the development of both the detection and the diagnosis phases. The issues which may arise during the development of the remedy phase are also discussed.

The detection phase consists of two components: The first, the modified black spot, considers that, from a highway agency's perspective, accidents which occur due to road related factors should have greater influence in identifying accident prone locations than those which occur due to driver or vehicle related factors. The basic idea is to classify accidents according to their patterns and contributing factors into one of the three groups of the highway system (the driver, the vehicle, and the road environment). A fuzzy pattern recognition algorithm is used for the classification process. Locations are then identified
as accident prone if they exhibit a significant number of correctable (e.g. road related) accidents. The second component of the detection phase, the countermeasure-based program, attempts to identify locations which can be cost effectively treated irrespective of their total number of accidents. The approach reverses the traditional process by first identifying main accident patterns that can be targeted by specific countermeasures and then searching for locations which have over-representation of these patterns. The approach utilizes the Empirical Bayes technique for the identification process. Case studies are used to demonstrate the usefulness of the two programs. In the diagnosis phase, a prototype knowledge-based system is developed to identify the causes and the contributing factors of accidents at the locations identified in the detection phase. The output of the diagnosis phase is a set of applicable countermeasures for each accident prone location and the degree of belief in each countermeasure. The prototype knowledge-based system was validated using several case studies which demonstrated satisfactory results.

Finally, several recommendations for further research in selected areas to further enhance the system are introduced.
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Finally, I would like to dedicate this thesis to my parents whose love and support throughout my life made me achieve this cherished goal.
CHAPTER 1
INTRODUCTION

1.1 THE PROBLEM

Traffic safety has been a serious concern since the start of the automobile age, approximately eleven decades ago. In spite of this concern, traffic safety problems have prevailed over the past century causing enormous economic and social costs. It is commonly accepted that there are many costs associated with vehicular mobility such as air pollution, noise, visual intrusion, accidents, as well as others. However, the economic and social costs associated with road accidents greatly exceed other mobility costs due to the pain, grief, loss of property, injury, and deaths attributed to road accidents.

Worldwide, about half a million people are killed in road accidents each year (Hutchinson, 1987). In the US, more preretirement years of life are lost due to road accidents than from the combined effects of the two leading diseases, cancer and heart disease (Evans 1991). The annual monetary cost of road accidents in the US is estimated at 74 billion dollars (National Highway Traffic Safety Administration, 1987). In Canada, about 4,000 persons are killed and 250,000 are injured annually as a result of road accidents (Canadian Motor Vehicle Traffic Collision Statistics, 1992). In British Columbia, there were 490 fatalities, about 53,000 injuries and 170,000 property damage only accidents in 1993. The direct annual cost to the province is conservatively estimated at 1.7 billion dollars (ICBC, 1993). Consequently, the importance of reducing the social and economic costs of road accidents can not be overstated.
Recognizing the traffic safety problem and the importance of reducing the frequency and severity of road accidents, the majority of road authorities have established Highway Safety Improvement Programs (HSIPs). The steps and procedures which should be followed in these programs were given great attention by several highway agencies and several manuals were published describing these procedures. However, there are two problems with carrying out HSIPs as described in these manuals. First, it takes a great deal of time and efforts given the size of the accident database which make their automation a very desirable goal.

Second, and more important, the manuals primarily focus on the type of studies needed to be performed, and the statistical techniques to identify accident prone locations and to estimate the effectiveness of safety improvements. Less attention has been devoted to improve our understanding of accident causes and contributing factors. This is unfortunate, given the lack of complete understanding of the complex interaction of accident factors and how safety measures work. Statistical analysis is an integral part of accident research, however, a better understanding of the problem is required before attempting to apply any statistics.

Accidents represent instances in which the road system has failed, yet our understanding of the failure mechanism is poor, thus reducing the accuracy of the diagnosis and remedy processes. Normally, there is enough data in most accident databases to allow for better understanding of the many factors which contribute to accidents. The problem, however, is the lack of efficient methods to analyze this data.
Evans (1993) writes:

"Basically, traffic safety is one of many fields that can be characterized as data rich, understanding poor. The main thing that has been missing from traffic safety research is the appropriate scientific tradition to extract meaning from copious data that already exists; the answers to many key questions are embedded in existing data."

Given all these difficulties, there is a recognized need for research which focuses on improving our understanding of the interaction between accident factors and their relation with engineering countermeasures. The goal of the research should be the development of effective analytical techniques which are capable of analyzing large scale databases to identify links between different accident contributing factors and establishing countermeasures.

1.2 THE HIGHWAY SAFETY EXPERT SYSTEM

This thesis describes the development of a highway safety expert system. The objective of the system is to provide highway safety officials with an efficient and reliable tool to identify accident prone locations and then quickly and reliably advise on the appropriate countermeasure(s) based on an analysis of the accident and roadway environment data.

Traffic safety problems are ill-structured, poorly understood, and lack explicit algorithms for analysis. These characteristics suggest that the expert system approach would be effective. Several researchers such as Spring et al. (1987), recognized the need for such a
system and demonstrated its feasibility. Several efforts were undertaken to build expert systems directed to solve particular safety problems (Seneviratne, 1990; Zhou et al., 1991). However, these efforts stopped short of producing operational systems. They recognized the complexity and size of the problem compared with the resources and time available. The reason for the limited success of these efforts is that they attempted to produce systems that can be a replacement for the safety engineer. Although this goal may be feasible, it would need huge resources and efforts.

The system described in this thesis is in no way intended to eliminate the involvement of the safety engineer in the process, but rather to relieve him of many of the routine analytical tasks. The main advantage of the system is its ability to process a large amount of accident data, separating locations which are most promising to be treated by engineering measures and providing advice on the countermeasures and their expected effectiveness. The system also provides an enhancement to many of the techniques currently used in highway safety improvement programs including two new methods for identifying accident prone locations.

The system consists of three basic phases as shown in Figure 1: Detection, or "where are the safety problems?"; Diagnosis, or "what causes the safety problems and what are the applicable countermeasures?"; and Remedy, or "what countermeasure(s) is effective to alleviate the safety problems?". The three phases comprise the main components of highway safety improvement projects. This thesis describes the development of both the detection and the diagnosis phases. The issues which may arise during the development of the remedy phase are also introduced. The detection phase for this system consists of two components. The first is the "modified black spot program" which considers accident
correctability by engineering measures. Accident correctability is assessed utilizing a fuzzy pattern recognition algorithm. The second is the "countermeasure-based-program" which primarily considers locations that have a well defined patterns of accidents. Accident patterns are assessed using the Empirical Bayes technique. In the diagnosis phase, a prototype knowledge-based system is developed to perform the analysis of the locations identified in the detection phase and advise on applicable countermeasures. The detection phase was implemented on BCSystem main frame computer because of the huge accident database, while the diagnosis phase was implemented on the PC.

1.3 THESIS STRUCTURE

Chapter One provides an overview of the thesis and its structure. The main concepts and terminology of highway safety improvement programs in general and the existing safety practice at the B.C. Ministry of Transportation and Highways will be described in Chapter Two. Due of the diversity of topics handled in this thesis (e.g. highway safety improvement programs, fuzzy pattern recognition, knowledge based expert systems, etc.), it was decided not to include one literature review chapter of all these topics. Rather, other needed literature review will be included with the chapter corresponding to the relevant topic. The detection phase of the system is described in Chapters Three and Four. Chapter Three describes the first program of the detection phase, the modified black spot program while Chapter Four describes the second detection program, the countermeasure based program. Chapter Five describes the diagnosis phase where a prototype knowledge based system is developed to analyze accident prone locations. Chapter Six briefly discusses the issues which may arise during the development of the
remedy phase and directions for further research requirements while Chapter Seven is the summary and conclusion.

A final note regarding the terminology used in this thesis is important. There has been increasing criticism of the use of the word "accident" and many researchers prefer to use other words such as "crash" or "collision". They argue (Langely, 1988 and others) that "accidents" conveys a sense that the losses incurred are due to fate and devoid of predictability. Although, this argument may be legitimate, the word "accidents" is used in this thesis because it is the common word used in the literature and because the techniques developed in this thesis are intended for use by practicing safety engineers who are more familiar with using the term "accident".
Figure 1.1 The Highway Safety Expert System Components
CHAPTER 2

LITERATURE REVIEW

2.1 HIGHWAY SAFETY IMPROVEMENT PROGRAMS

Recognizing the importance of reducing the number and severity of road accidents, the majority of road authorities have established Highway Safety Improvement Programs (HSIPs). The main goal of these programs is to identify locations that may have safety problems (accident prone locations) and establish countermeasures to correct them. In broad terms, the development of HSIPs involves the following functions:

- Continuous monitoring of the road network to identify accident prone locations (APL),
- Analysis of the identified locations to find out what causes them to be accident prone, and
- Given these locations and their problems, what countermeasures are effective to alleviate the problem.

The procedures followed to carry out these functions were given great attention by researchers and several manuals which describe them in detail were produced. The following sections provide description of these procedures.

2.1.1 The Identification of Accident Prone Locations

Programs to identify accident prone locations are usually called "Black Spot Programs". The basic assumption of these programs is that the road design plays a contributory role
in the occurrence of many road accidents. Thus, improving the engineering elements of
accident prone locations can avert a significant proportion of accidents. A problem
location may be defined as an intersection or a section. These locations are usually
considered in subcategories of the road system. Different categorization criteria are often
used which include, whether the location in an urban or rural area, and the road class (e.g.
freeway, arterial, collector, etc.).

In accident black spot programs, an accident prone location is defined as any location
(section or intersection) that exhibits a higher potential for accidents than an established
"norm". The higher potential for accidents can be expressed in terms of any accident
measure such as accident frequency, rate, severity or a combination of frequency and rate.

Selecting the section length and the time period for which accident data are accumulated
to calculate accident measures is a controversial issue. For example, as the length of road
gets very small, the probability of zero or one accident tends toward unity. As the length
of road gets very large, the effect of isolated hazards will be submerged and lost. Zegeer
(1982), states that "accident rates in accidents per million vehicle miles become unstable
and of questionable value for highway segments of short length (i.e. less than 0.3 miles)
even when several years of accidents and volume data are used." Nicholson (1980)
recommended the avoidance of sections shorter than one kilometer.

The choice of time is also controversial. The shorter the time period, the greater the
probability of quickly detecting sudden changes in the accident occurrence. However,
statistical reliability considerations indicate that a longer time period is required, while
longer periods would prevent the quick detection of changes in accident rates. A time
period of one to three years is commonly used in most road jurisdictions (Zegeer, 1982).
The following are a description of the methods most commonly used to identify accident prone locations:

2.1.1.1 The Frequency Method

This method uses accident frequency (AF), defined as the number of accidents per location during a specific time period, to identify APLs. If the observed AF meets or exceeds a predefined value, the location is considered accident prone. Several different section lengths and/or years of data are often used. The predefined frequency criterion usually varies by area type (urban/rural) or other variables such as highway class. Proponents of the frequency method argue that locations identified by this method have a high number of accidents and consequently have a higher potential for accidents reduction. The problem with using the frequency method, however, is that it does not account for the exposure effect. For example, 10 accidents per km may be considered "high" for a section that carries 15,000 veh/day, and "low" for another section that carries 40,000 veh/day

2.1.1.2 The Rate Method

The rate method uses the accident rate (AR), defined as accidents per million-vehicle-kilometers (mvk) for sections, and accidents per million-entering-vehicle (mev) for intersections:

\[
AR = \frac{N \times 10^6}{L \times \text{AADT} \times t \times 365}
\]  

(2.1)
Intersections:

\[ AR = \frac{N \times 10^6}{AADT \times t \times 365} \quad (2.2) \]

where

- \( N \) = Number of accidents observed during period \( t \),
- \( L \) = Segment length (km),
- \( AADT \) = Average Annual Daily Traffic volume (veh/day), counting all approaches in the case of intersection, and,
- \( t \) = observation period (years).

The method requires the availability of a traffic volume file. The volume file should be formatted by a compatible location reference method as the accident file. Locations that meet or exceed a predefined accident rate are then identified as accident prone.

Although the use of \( AR \) addresses the exposure effect, it introduces another bias in the identification of accident prone locations when applied to low volume roads. For example, 2 accidents per year may be considered low from a frequency point of view, however, on a low volume road, it may result in a high accident rate (e.g. for 1 km section and 1 year period, 2 accidents will result in \( AR \) greater than 2.0 if the traffic volume is less than 2700 veh/day).

2.1.1.3 The Frequency Rate Method

To address the weakness of using either the rate or the frequency methods, several researchers such as Zegeer and Deen (1977) and Renshaw and Carter (1981) suggested using both \( AF \) and \( AR \) to identify accident prone locations. Usually, locations that meet the frequency criteria is first selected and then ranked using the rate criteria. However,
some agencies use the rate to select locations and the frequency for ranking. Other agencies, define a double criteria where a location must meet or exceed both predefined accident frequency and rate.

2.1.1.4 The Severity Method

The severity method uses the Accident Severity Ratio (ASR), defined as the weighted proportion of fatal (F), injury (I), and property-damage-only (PDO) accidents to the total number of accidents (TOT):

\[
ASR = \frac{100 \times F + 10 \times I + PDO}{TOT}
\]  

(2.3)

Because all accidents are weighted against the PDO accident, the ASR is also known as Equivalent PDO (EPDO). For example, if the portion of F, I, and PDO accidents at some location is 1%, 33% and 66%, the ASR value would be equal to 4.96. Various jurisdictions use different weights than the 100, 10, and 1 shown above. However, the ASR is an arbitrary ratio that relates the proportions of accidents with various severity levels at a given location and any convenient weighting will do.

Locations are ranked by their EPDO and those that meet or exceed a certain threshold value are selected. In some jurisdictions an EPDO rate is calculated by dividing the EPDO by the traffic volume to account for exposure.
2.1.1.5 Classical Statistical Techniques to Identify APLs

High frequency of accidents may not necessarily mean that a particular location is truly accident prone. This high frequency may be solely caused by random variations of accident occurrence. An optimal identification technique would only identify locations that are truly accident prone and would not identify any non accident prone locations. To address this concern, many classical statistical techniques have been developed and used to identify accident prone locations based on historical accident data. Typically, a location will be identified as accident prone if its observed accident measure exceeds some critical level. The simplest method to calculate this critical level is the confidence interval based technique in which the critical level is equal to the sample mean plus a multiple of the sample standard deviation. The multiple coefficient depends on the degree of confidence desired and is based on the assumption that the sample follows the normal distribution. The most widely used statistical technique among highway agencies, however, seems to be the rate quality control technique (Nordon 1956), which is based on statistical quality control procedures.

The Rate Quality Control Technique

The rate quality control technique defines a location as accident prone if the observed number of accidents exceeds a critical number or if the observed accident rate exceeds a critical accident rate. The main assumption of the technique is that the number of accidents occurring at a given location during a given time period can be approximated by the Poisson distribution. This assumption is widely accepted among safety researchers
and has been investigated many times and turns out to be supported by a vast body of empirical evidence (Oppe 1982; 1992).

Based on the Poisson assumption, then:

\[ P(n) = e^{-a} \frac{(a)^n}{n!} \quad (2.4) \]

where

- \( P(n) \) = probability that \( n \) accidents will occur at a given location during the given time period, and
- \( a \) = expected number of accidents at the given location during the given time period.

Equation 2.4 can be also written as:

\[ P(n) = e^{-\lambda m} (\lambda m)^n / n! \quad (2.5) \]

where

- \( \lambda \) = expected accident rate in accidents per million vehicle kilometers and
- \( m \) = number of vehicle kilometers in million.

The value for \( a \) and \( \lambda \) are taken to be the average number/rate across all similar locations in a specified region.

Based on Equation 2.5, an upper control limit \( U \) can be calculated such that:

\[ \text{Probability} \ (X \geq U) = P \quad (2.6) \]

where

- \( X \) = the observed number of accidents,
\[ P = \text{predefined probability limit.} \]

The upper control limit (the critical limit) can then be calculated using a table of Poisson distribution. However, calculating the upper control limit from these tables involves double interpolation (for \( a \) and for \( X \)). Nordon (1956) obtained satisfactory approximations to determine the critical rate or number by using:

\[
CN = a + k\sqrt{a} + 0.5 \tag{2.7}
\]

\[
CR = \lambda + k\sqrt{\lambda} \frac{1}{m} + \frac{1}{2m} \tag{2.8}
\]

where \( k \) is a constant related to the probability \( P \) as follows:

<table>
<thead>
<tr>
<th>( P )</th>
<th>Level of Significance</th>
<th>( K )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0001</td>
<td>0.01%</td>
<td>3.719</td>
</tr>
<tr>
<td>0.0005</td>
<td>0.05%</td>
<td>3.290</td>
</tr>
<tr>
<td>0.0010</td>
<td>0.1%</td>
<td>3.090</td>
</tr>
<tr>
<td>0.0050</td>
<td>0.5%</td>
<td>2.576</td>
</tr>
<tr>
<td>0.0100</td>
<td>1%</td>
<td>2.326</td>
</tr>
<tr>
<td>0.0500</td>
<td>5%</td>
<td>1.645</td>
</tr>
<tr>
<td>0.1000</td>
<td>10%</td>
<td>1.282</td>
</tr>
</tbody>
</table>

Locations that have a higher accident number or accident rate than the \( CN \) or the \( CR \) are considered to be accident prone since their deviations from their expected means can not be reasonably attributed to the random fluctuation in accident occurrence.

2.1.1.6 Selection of the Identification Method

Most jurisdictions utilize more than one method to identify accident prone locations. It is common to use the rate quality control method in conjunction with the accident frequency
method. Although the accident frequency method does not account for exposure, it is useful to exclude locations with low numbers of accidents before applying the rate quality control method and calculating critical rates. It is also important to use the accident severity method as a supplemental method (Zegeer, 1982) since the existence of severe accidents (injury and fatal) should justify a further analysis of locations than property damage only accidents.

2.1.2 Bayesian Analysis of Accident Data

In the rate quality control technique, the expected number of accidents at a site was considered to be a deterministic value. Nordon (1956) acknowledged this assumption in the derivation of the rate quality control formula. He stated that the true expected accident number for a certain location is never known and shall always have to be satisfied with an estimate.

In reality, the expected number of accidents at a site is a random variable itself which fluctuates around some unknown mean. This is the reason that historical accident data at a location do not always reflect long-term accident characteristics accurately. For example, a location that has low accident rates during long periods of time may have had high accident rates during portions of this period. This random variation can be accounted for by providing correction for a statistical phenomenon called regression to the mean (RTM). This phenomenon refers to the tendency of extreme events to be followed by less extreme values, even if no change has occurred in the underlying mechanism which generates the process. To illustrate the RTM effect, consider a hypothetical site with annual accident frequency varying around a mean of seven crashes
Literature Review

per year as shown Figure 2.1. Consider two points which greatly deviate from the average (i.e. 1986 and 1988), both have regressed towards the mean in the subsequent year without any change to the accident occurrence process (e.g. treatment). The effect of this phenomena has been acknowledged for some time (Hauer, 1980; and Hauer and Persaud, 1984). The type of analysis suggested to account for this problem is the Bayesian Analysis. It provides a formal mechanism for combining information drawn from different sources in a single analysis. The advantage of Bayesian analysis is that it regards accident measures at any location as random variables, and combines regional accident characteristics with the location specific accident history to identify the distributions of accident characteristics at each location and estimate their parameters.

Bayes' theorem can be mathematically stated as follows:

if a certain parameter \( \phi \) has a prior distribution \( P(\phi) \) and that for a specific value of \( \phi \), the probability of making \( x \) observations is given by \( P(x|\phi) \). The posterior distribution \( P(\phi|x) \) of \( \phi \) which represents the resolution of the prior given the observations is given by:

\[
P(\phi|x) = \frac{P(x|\phi) \times P(\phi)}{\sum P(x|\phi) \times P(\phi)}
\]

Typically, the observation distribution will be assumed to be a Poisson or binomial distribution and the prior distribution a gamma or beta distribution (Calvin, 1990). The main issue then is how to estimate the parameters of the prior distribution. In a pure Bayesian analysis, these parameters are usually assumed based on engineering judgment and past experience, while in the Empirical Bayes approach, the parameters are estimated using a sample of observations from population of similar locations (the same kind as the one being investigated).
Figure 2.1 Regression to the Mean effect
2.1.2.1 The Empirical Bayes Technique

The Empirical Bayes approach has been used by several researchers in accident analysis. Hauer (1986) estimated the expected number of accidents occurring at a certain location using data for similar locations. Wright et al. (1988) and Mountain and Fawaz (1989) used the approach to de-bias the "before" and "after" studies of accident countermeasures. Higle and Witkowski (1988) described an Empirical Bayes procedure to identify accident prone locations. This procedure will be introduced since it is the most relevant to the work reported in this thesis.

The following notations are used:

\( \tilde{\lambda}_i \) = accident rate at location \( i \) (treated as a random variable),
\( N_i \) = number of accidents at location \( i \) during the period of time in question,
\( V_i \) = number of vehicles passing through location \( i \) during the period of time in question,
\( f_i(\lambda|N_i,V_i) \) = probability density function associated with the accident rate at location \( i \) given the observations \( N_i \) and \( V_i \) (posterior distribution), and
\( f_R(\lambda) \) = probability density function associated with the accident rate across the region (the prior distribution).

The assumptions made in the procedure are that:

1. At any given location, when the accident rate is known (\( \tilde{\lambda}_i = \lambda \)) the actual number of accidents at any given location follows a Poisson distribution with expected value \( \lambda V_i \). That is,

\[
P[N_i = n|\tilde{\lambda}_i = \lambda, V_i] = \frac{(\lambda V_i)^n}{n!} e^{-\lambda V_i}
\]

(2.10)
2. the probability distribution of the regional accident rate, $f_r(\lambda)$ is the gamma distribution which implies that

$$f_R(\lambda) = \frac{\beta^\alpha}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta \lambda}$$

where $\alpha$ and $\beta$ are parameters of the gamma distribution.

The first step then is to estimate the prior distribution parameters $\alpha$ and $\beta$. There are two main methods for estimating the parameters $\alpha$ and $\beta$. The simpler is the method of moments estimates (MME), where $\alpha$ and $\beta$ are chosen so that the mean and variance associated with the gamma distribution are equal to the mean and variance of the sample. That is if $\bar{x}$ and $s^2$ is the sample mean and variance of the observed accident rates, and $m$ is the number of locations under observations, then

$$\bar{x} = \frac{1}{m} \sum_{i=1}^{m} \frac{N_i}{V_i}$$

$$s^2 = \frac{1}{m-1} \sum_{i=1}^{m} \left( \frac{N_i}{V_i} - \bar{x} \right)^2$$

In the MME method, $\alpha$ and $\beta$ are selected so that

$$\beta = \frac{\bar{x}}{s^2}$$

$$\alpha = \beta \bar{x}$$

The other method is the maximum likelihood estimates (MLE) where $\alpha$ and $\beta$ are chosen to maximize:
The function $\Phi$ represents the likelihood function associated with the observed data. The MLE values for $\alpha$ and $\beta$ may then be obtained by solving the equations:

\[
\begin{align*}
\frac{\partial \Phi}{\partial \alpha} &= 0 \\
\frac{\partial \Phi}{\partial \beta} &= 0
\end{align*}
\]

(2.17)  
(2.18)

After estimating the values of $\alpha$ and $\beta$, the regional probability distribution (the prior distribution) is combined with the location accident rate to obtain the location specific probability density function, $f_i(\lambda|N_i,V_i)$ using Bayes theorem, i.e.

\[
f_i(\lambda|N_i,V_i) \propto f(N_i|\lambda, V_i) f_R(\lambda)
\]

(2.19)

According to Berger (1985), the resulting probability distribution $f_i(\lambda|N_i,V_i)$ is a gamma distribution with parameters:

\[
\begin{align*}
\alpha_i &= \alpha + N_i \\
\beta_i &= \beta + V_i
\end{align*}
\]

(2.20)  
(2.21)

And thus, the probability density function associated with the accident rate at location $i$ is given by:

\[
f_i(\lambda|N_i,V_i) = \frac{\beta_i^{\alpha_i}}{\Gamma(\alpha_i)} \lambda^{\alpha_i-1} e^{-\beta_i \lambda}
\]

(2.22)
Finally, location \( i \) will be identified as accident prone if there is a significant probability that the location's accident rate, \( \bar{\lambda}_i \), exceeds the observed regional accident rate, \( X_R \).

Thus, location \( i \) is identified as accident prone if:

\[
P\{ \bar{\lambda}_i > X_R \mid N_i, V_i \} > \delta
\]

or equivalently if:

\[
\left[ 1 - \int_0^{X_R} \frac{\beta^{\alpha_i}}{\Gamma(\alpha_i)} \lambda^{\alpha_i-1} e^{-\beta \lambda} d\lambda \right] > \delta
\]

where \( \delta \) represents the confidence level desired, such as 0.95, or 0.99.

The value of the regional accident rate, \( X_R \) is calculated using:

\[
X_R = \frac{\sum_{i=1}^{m} N_i}{\sum_{i=1}^{m} V_i}
\]

However, there is one observation on Higle's and Witkowski procedure concerning the way they calculate the variance of the regional distribution. They used Equation 2.13 based on the assumption that, \( \bar{\lambda}_i = N_i / V_i, i = 1, \ldots, m \), is their sample of observations. However, the sample observations should be a collection of paired values \((N_i, V_i)\) and thus the variance of the regional distribution should be (Hauer and Gardner 1986):

\[
s^2 = \frac{1}{m-1} \left[ \frac{\sum_{i=1}^{m} (N_i^2 - N_i)}{V_i^2} - \frac{1}{m} \left( \sum_{i=1}^{m} N_i / V_i \right)^2 \right]
\]

Although the Empirical Bayes method is considered statistically superior to the rate quality control method, it is not widely used among road agencies. The main reason for
the limited use is the complexity of the method. Many safety engineers are not familiar with the Bayesian analysis and it requires larger computational resources.

2.1.3 The Analysis of Accident Prone Locations

After accident prone locations (APLs) have been identified, the next step is to analyze these locations to identify the nature and cause(s) of the safety problem(s); and then identify the appropriate countermeasure(s). It is generally acknowledged in the literature that this analysis is not simple and that it involves considerable judgment by the analyst. To overcome some of the inconsistencies and subjectivity among analysts, many authorities have established detailed systematic approaches for the analysis of APLs. This analysis includes many procedures based on accident data, road environment data, traffic data, and driver behavior data. The following is a brief description of these procedures.

2.1.3.1 Accident Based Procedures

Accident based procedures include studying and analyzing accident data at accident prone locations to identify safety problems and their possible causes. The main accident characteristics examined include:

- **Accident types**

  Predominant accident types (patterns) at each site (e.g. right angle, fixed object, head on, etc.) are identified. These patterns serve as an indicator of the possible causes of the safety problems.
• **Accident severities**

Accidents are classified according to their severities into: fatal, injury and property damage only accidents. According to FHWA (1981), this analysis is conducted to assist in identifying safety deficiencies and in selecting countermeasures utilizing the severity characteristics of individual accidents.

• **Accident contributing circumstances**

This analysis is undertaken to identify possible accident causes based on the contributing circumstances as described by the police officer attending the accident scene. There are three main categories of contributing circumstances: driver related, road environment related and vehicle related. Based on this analysis, accident causes can be identified and possible countermeasures can be suggested. Another important use of this analysis is to determine the correctability of accidents by engineering measures.

• **Accident environmental conditions**

This analysis identifies accident causes related to environmental conditions, namely lighting conditions (day light, dusk, dark, etc.) and roadway surface conditions (dry, wet, snow, etc.). The output of this analysis is the percentage of accidents involving particular conditions (e.g. night accidents, wet pavement accidents, etc.) in the total number of accidents.
2.1.3.2 Road Environment Based Procedures

These procedures are undertaken to assess road environment conditions which may be contributing to the frequency and the type of road accidents. Road environment characteristics examined usually include road geometry (e.g. lane widths, shoulder widths, sidewalks, medians, etc.), pavement condition (e.g. skid resistance), and lighting conditions. According to FHWA (1981), the main road environment-based procedures include:

- **Roadway inventory study**

  In this study the dimensions of the roadway and the roadside (e.g. lane widths, shoulder widths, sidewalks, medians, etc.) are obtained. This procedure is very important in determining accident causes and insuring that the countermeasure(s) selected for the site is appropriate.

- **Sight distance study**

  This study is used to measure sight distance along an intersection or road section to see whether it is adequate. It is well established in the literature that many accident patterns are connected to the adequacy of sight distances (Institute of Transportation Engineers, 1982; FHWA, 1981). There are four types of sight distances; stopping sight distance which is the minimum sight distance required to safely react and stop in response to unsafe condition; decision sight distance which is the distance required to detect an unexpected hazard and initiate and complete the required safety maneuver safely and efficiently; and intersection sight distance which is the minimum distance required to safely respond to crossing traffic; and passing sight distance which is the minimum distance required to safely pass another vehicle on a two-lane highway.
• **Skid resistance study**

The need for this study is usually based on over-representation of "wet weather" accidents. Skid resistance describes the level of friction between the roadway surface and the vehicle tire when the tire is prevented from rotation. There are different measurement modes for measuring skid resistance. The most common method is the locked wheel braking mode which measures the force required to pull a specified tire, while it is prevented from rotation. Other modes include the slip mode and the YAW mode (FHWA, 1978). The results of the skid resistance test is compared to pre-established standards based on vehicle travel speeds.

• **Lighting study**

This study is usually warranted based on over-representation of night-time accidents compared to similar sites. It can be undertaken to provide lighting facilities or improve existing facilities. There are several techniques to conduct this study such as AASHTO, 1984; and Walton and Rowan, 1974. The major considerations for each technique can be found in (FHWA, 1981).

### 2.1.3.3 Traffic Based Procedures

These procedures study the traffic characteristics of the location. The main characteristics usually considered are traffic volume, speed, travel time and delay, and gap studies. The findings of these studies are used in conjunction with accident data to determine safety deficiencies and identify reliable traffic countermeasures.
• **Traffic volume study.**

The objective of the volume study is to determine the number and movement of vehicles and pedestrians at the location. The volume data is used to reflect the level of service and the location's ability to serve the traffic demand.

• **Spot speed study**

This study is used to determine the speed distribution of a traffic stream at the location. It is well established in the literature that many accident patterns may be caused by high speed. These patterns include: right angle and left-turn accidents at intersections, head-on and run-off-road at curve sections, and severe accidents at all locations. The speed study output is used to justify the need for countermeasures such as increased enforcement of speed limit, etc.

• **Travel time and delay study**

This study is usually undertaken at locations where accident patterns reveal congestion related accidents (rear-end, right angle, and left turn accidents). These types of accidents are usually of minor severities as they occur during high traffic volume and low speeds conditions. The results of these studies is also very important in the economic analysis of safety countermeasures which have an effect on travel time and delay.

• **Gap study**

This study is used to measure the time headway between vehicles on a traffic stream. The gap study is usually undertaken at locations having accidents involving merging or crossing traffic. Accident patterns that are usually related to gap availability are
sideswipe and rear-end accidents at freeway ramps, pedestrian accidents and crossing and merging accidents at signalized and unsignalized intersections. The study results are usually used to justify additional traffic controls.

2.1.3.4 Driver Behavior Based Studies

Driver related factors plays a very important role in the majority of accidents. It is estimated that about 95% of all accidents involve some driver related contributory factors. Therefore, information about driver behavior at accident prone locations (e.g. evasive actions, curves negotiation, etc.) can be very important in determining accident causes at these locations. This information may be obtained using traffic conflict studies. Conflict studies involve the collection and analysis of traffic conflicts. A traffic conflict is a situation in which a driver has to take an evasive action to avoid a possible collision. OECD (1976) suggests that conflict studies can be useful in:

- Identification of accident prone locations
- General diagnosis of accident causation
- Developing countermeasures at particular sites

It should be noted, however, that defined relations between conflicts and accidents have not been well established in the literature and that caution should be taken in the analysis of conflict data as it involves considerable judgment by the observer.
2.1.3.5 Identify Safety Deficiencies

After accident analysis procedures have been performed, the data is assembled and used by the analyst to identify safety deficiencies at the location. Each of the possible accident causes derived from the procedures are assessed and a list of probable causes are identified. The list is used to develop countermeasures. However, the identification of accident contributing factors (causes) is not simple. The main difficulty is the complex interaction between these factors. Rarely can an accident be attributed to a single contributing factor or cause. The analyst must utilize his knowledge and experience to identify accident causes.

2.1.3.6 Selection of Countermeasures

Similar to identifying accident causes, the decision on the choice of the countermeasure(s) is usually made based on engineering experience and judgment. OECD (1976) states:

"No simple formula can be drawn up to define the crucial step from diagnosis of problem areas to selection of treatment. This decision must be made by the engineer, based on his experience and judgment."

In making these judgments, many analysts do not rely on a formal detailed analysis but instead utilize their knowledge of the countermeasures and previous experience with their use. However, to aid in the selection process, there are several publications which attempted to document the general "rules of thumb" used in analyzing accident data at specific locations and the list of possible countermeasures. OECD (1976) for example,
provides a comprehensive list of countermeasures classified into five categories: geometric design, road surfaces, road markings and delineation systems, road signals and furniture, and traffic management. Discussion is also provided regarding the possible use of these countermeasures and accident types that can be avoided by their implementation. Similar efforts can also be found in FHWA, 1981; NAASRA, 1988; and Box, 1976.

2.1.4 Economic Evaluation of Countermeasures

An important issue in the development of any highway safety improvement program is the cost-effectiveness of the entire program. After identifying all the countermeasures that have the potential to reduce the number and/or severity of accidents at each accident prone location, their economic feasibility must be demonstrated before they can be implemented. This is achieved by performing an economic analysis of these countermeasures.

Methods for economic analysis of countermeasures is mainly divided into two categories. The first category involves these methods which provide a quantitative assessment of the economic benefits of countermeasures using a common measurement (dollars). In these methods a dollar value is assigned to fatal, injury and property damage only accidents. Three main methods fall in this category; benefit/cost ratio method, rate of return method and payback period method. The second category is the cost-effectiveness method which does not put a dollar value on accidents.

All these methods are well documented in the literature with the benefit-cost ratio analysis being the most popular among these methods. In a benefit-cost analysis, the ratio
between the present value of benefits and the present value of countermeasure costs is called a benefit to cost (B/C) ratio. The B/C ratio is calculated for each project (a countermeasure or a set of countermeasures). Projects that have B/C ratio greater than one are considered economically feasible. However, having a B/C ratio greater than one does not automatically justify a project. Various projects often have to compete for a limited budget. In this case, projects are ranked according to their B/C ratio. Projects are then selected from the ranked list in descending order. If the addition of a project makes the cumulative cost exceeds the budget, the project is skipped, and other projects down the list are selected. This process is repeated until no further projects can be selected.

This process does not completely optimize the selection of projects that have the highest return and other procedures such as dynamic programming and integer programming can be used for this purpose. However, they need much larger computational resources compared with the B/C procedure.

The cost of a countermeasure include initial implementation costs (e.g. right of way acquisition, construction, etc.), and the operating and maintenance costs. Usually, highway agencies maintain average estimates for these costs. However, in many cases, project costs are greatly affected by the site-specific factors such as topography, right of way availability, and drainage requirements. In this situation specific project cost data should be provided to improve the accuracy of the results. The benefits can mainly be divided into operational and safety savings. Operational savings include savings in travel time and savings in vehicle operating costs. Safety savings are represented by the estimated reduction in the number and/or severity of accidents following the implementation of the improvement. The safety savings usually comprise the main portion of the benefits.
Accident reduction capabilities of countermeasures are usually estimated using what are known in the literature as Accident Reduction (AR) factors. Several agencies such as FHWA and ITE have developed AR values for different countermeasures on a system-wide basis based on past and current evaluation research and safety projects. These values are commonly expressed as a percentage reduction in the total number of accidents. However, in some cases, AR factors may be available for different accident types and severity classes. The benefits of a countermeasure is calculated using the following formula (FHWA, 1981):

\[
\text{Accidents prevented} = N \times AR \times \frac{(ADT \text{ after period})}{(ADT \text{ before period})}
\]

where:

- \(N\) = expected number of accidents without implementing the countermeasure,
- \(AR\) = accident reduction factor (percent),
- \(ADT\) = average daily traffic volume (veh/day).

In case of multiple improvements, the accident reduction factor will be a combination of the individual reduction factors:

\[
AR_M = AR_1 + (1 - AR_1)AR_2 + (1 - AR_1)(1 - AR_2)AR_3 + ...
\]

where:

- \(AR_M\) = overall accident reduction factors for multiple improvements (mutually exclusive) at a certain location.
2.1.4.1 Assigning Values to Accidents

As previously noted, many of the methods for the economic analysis of countermeasures assign a value to different accident severity classes. These values are based on the direct and indirect accident costs to society. There is little agreement in the literature regarding what constitutes these two costs, especially the indirect costs. Direct costs are the costs of goods and services consumed as a result of accidents. These costs include; property damage, emergency medical and transportation service costs, medical treatment costs, and legal and court costs. Indirect costs value all changes and irretrievable losses experienced by people involved in accidents and by society (Kragh et al., 1986). These costs may include the costs of goods and service that individuals will not be able to produce or perform because of accidents and other intangible costs such as pain and suffering. The disagreement on what constitutes indirect accident costs led to two approaches to estimate accident costs, the willingness to pay approach and the human capital costs approach. The willingness to pay approach attempts to comprehensively measure many intangible benefits such as the value individuals place on their lives which include pain and suffering and quality of life. The human capital cost approach, on the other hand, measures the losses which are real costs to society both external and internal to the individual. Accident costs estimated by the human capital cost approaches are significantly lower than those estimated by the willingness to pay approach. The use of the willingness to pay approach has been on rise in the past few years as increasing criticism is directed to the Human Capital cost approach. A recent estimate of accident costs using both approaches in British Columbia is given in Table 2.1.
2.2 ACCIDENT DATA IN BRITISH COLUMBIA

As mentioned earlier, traffic accidents pose a significant problem for the province of British Columbia. In 1993, the direct costs of traffic accidents were conservatively estimated at 1.7 billion dollars. To address the problem of traffic accidents effectively, reliable and comprehensive accident data is required. Accident data serves many purposes including identification and ranking of accident prone locations, supporting expenditures for accident reduction improvements, before and after studies of improvements, and identifying the need for other non-engineering measures such as enforcement and driver education. The purpose of this section is to describe the current data collecting system in British Columbia and outline the characteristics of the MV104 police accident report form, which is the principal tool used to collect information about traffic accidents. Finally, some common problems associated with accident data are briefly discussed.

2.2.1 Accident Reporting Practices

According to the motor vehicle act, an accident report is required "where a motor vehicle driven or operated on a highway, either directly or indirectly causes death or injury to a person or damage to property causing aggregate damage $1,000 in case of a vehicle other than a motorcycle and $600 in the case of a motorcycle...". The person responsible for reporting the accident is the driver. Not all accidents are attended by the police. They usually attend severe accidents and accidents that cause interruption to traffic flow. If the police attended the accident scene, the police officer is required to complete a motor vehicle report form (MV104) which describes the accident circumstances and the characteristics of the person(s) and vehicle(s) involved. If the accident was not attended...
by the police, the driver is required to provide information to complete the MV104 form at the police office.

2.2.2 The MV104 Report Form

The MV104 is the principle tool used to collect information regarding traffic accidents in British Columbia. The report, shown in Appendix A, contains about 100 pieces of information which describe the characteristics of the accident and the person(s) vehicle(s) involved. The information on the MV104 can be divided into the following categories (TIRF, 1993):

- Collision descriptions;
- Descriptions of persons involved, including data on drivers, passengers and pedestrians;
- Involved vehicle descriptions
- Environment descriptions, including weather and road conditions; and
- Event sequence and contributory factors.

To facilitate the collection of such a large number of variables, a template is provided with the MV104 form (Appendix A). The template contains the coding scheme for the variables in the form. For example, the variable road type which is given the code #4 and which has seven choices (Asphalt, Gravel,...etc.) is recorded in box #4 in the template. Thus, an accident which occurred on an asphalt road will have the value "01" in box #4 in the template, and so forth.
A copy of the MV104 form is sent to the Motor Vehicle Branch which is responsible for maintaining records on traffic accidents. The data on the MV104 forms received by the Motor Vehicle Branch is entered to the Traffic Accident System (TAS) maintained at the B.C. Systems Corporation Data Center. In addition, all accidents reports are microfilmed and stored permanently.
<table>
<thead>
<tr>
<th>Accident Type</th>
<th>Human Capital Cost</th>
<th>Willingness to pay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fatal Accident</td>
<td>CDN$1,000,000</td>
<td>CDN$2,900,000</td>
</tr>
<tr>
<td>Injury Accident</td>
<td>CDN$35,000</td>
<td>CDN$100,000</td>
</tr>
<tr>
<td>Property Damage Only Accident</td>
<td>CDN$5,000</td>
<td>CDN$6,000</td>
</tr>
</tbody>
</table>
2.2.3 The Ministry of Transportation and Highways: Highway Accident System (HAS)

The Highway Safety Branch of the Ministry of Transportation and Highways is responsible for monitoring and improving traffic safety on provincial highways. This is achieved using a special database named the Highway Accident System (HAS). The database contains information provided by the Motor Vehicle Branch for traffic accidents on all provincial highways. The database is referenced by a location code. This is very important to identify locations which have safety deficiencies on the provincial highway system. The location code consists of three fields: highway number and letter; highway segment number which is defined in the landmark kilometer inventory, and kilometer distance. The database also includes exposure data (traffic volume counts) in order to calculate accident rates. HAS provides a data retrieval system which allows the user to construct and run jobs on the B.C. System mainframe computer to generate different statistical reports, accident rate tables and frequency which are used to identify accident prone locations, histograms (fatal, injury and property damage only accidents at each location). User-written SAS programs may also be included in a data retrieval job, allowing custom reports and specialized subset creation.

2.2.4 Problems with Accident Data in British Columbia

This section discusses problems and issues related to the use of accident data in British Columbia. These problems are not confined to British Columbia alone but are considered characteristic of almost all accident databases. Two areas are discussed: 1) problems with the completeness of accident data, and 2) problems with the accuracy of accident data.
2.2.4.1 Problems with Accident Data Completeness

The completeness of accident data has been a major concern for accident analysts (Hauer and Hakkert, 1988; James, 1991). A recent report concerning accident data in British Columbia (TIRF, 1993) identified two main problems related to accident data completeness. First, no agency routinely compiles all reports and records for all collisions in the province. This implies that accident databases based on police reports may be incomplete. Another dimension to the problem is that many minor collisions are not reportable because they are under the threshold reporting limit ($1000 in B.C). Consequently, the magnitude of the safety problem may be underestimated. Secondly, MV104 forms are not always filled in completely. Police leave some data fields on the form blank, resulting in incomplete accident records. The problem is more severe for accidents not attended by police officers where drivers or other involved persons are required to make reports on the accident at the police station. In many cases, there are discrepancies between different individuals involved in the accident causing much of the information to be rejected.

2.2.4.2 Problems with the Accuracy of Accident Data

The identification of safety problems and allocation of safety funds are tied up with available accident data. Thus, accurate accident data is very crucial for the success of any safety improvement program. Unfortunately, however, there are many concerns regarding the accuracy of the information in most accident databases. The accuracy of much of the information collected in accident reports relies mainly on the judgment and the
observational skills of the police or the person reporting the accident. Hamilton and Pinili (1992) completed a study to assess the accuracy of police-reported data in British Columbia. Their findings illustrated that police officers apply different rules in coding key information on MV104 report forms leading to significant data inconsistencies. They indicated the need for a greater degree of standardization to police officer's interpretation of MV104 forms.

2.3 CONCLUSION

Highway Safety Improvement programs involve three main processes: the identification of accident prone locations; the analysis of the causes and contributing factors of the safety problem and the selection of appropriate countermeasures; and finally the economic analysis of countermeasures to demonstrate their cost effectiveness. The identification process is undertaken using different statistical techniques (classical and bayesian) to identify locations which have higher potential for accidents than an established "norm". Accident contributing factors and causes are not considered in the identification process. The analysis of accident causes and the selection of countermeasures is usually made based on engineering experience and judgment which may include inconsistencies and subjectivities. However, there are several publications which attempt to document the general "rules of thumb" used in performing these processes. Methods for economic evaluation of countermeasures are well-documented in the literature with the benefit-cost ratio analysis being the most popular among these methods. Accident reduction capabilities of countermeasures are estimated using Accident Reduction (AR) factors. Several highway agencies have developed AR values
for different countermeasures on a system-wide basis based on past and current evaluation research and safety projects.

Finally, there are two main problems concerning accident data: completeness and accuracy problems. The completeness problem causes the magnitude of the safety problem to be underestimated while the accuracy problem leads to significant data inconsistencies.
CHAPTER 3

THE DETECTION PHASE: A MODIFIED BLACK SPOT PROGRAM

3.1 INTRODUCTION

The detection phase is concerned with the identification of locations that may have safety problems or that are deemed hazardous. These locations are usually called accident prone locations (APLs). In the classical black spot program, an accident prone location is defined as any location (section or intersection) that exhibits a higher potential for accidents than an established "norm". As shown in Figure 1.1, the detection phase for this system consists of two components. The first is the "modified black spot program" which considers accident correctability by engineering measures. The second is the "countermeasure-based-program" which primarily considers locations that have well defined patterns of accidents. This Chapter describes the modified black spot program in detail and provide examples for its applications to the identification of accident prone locations in British Columbia. The countermeasure based approach will be described in Chapter 4.

3.2 THE MODIFIED BLACK SPOT PROGRAM

As described in Chapter 2, the identification of APLs involves the calculation of different accident measures such as accident frequency and rate. Traditionally, the total number of accidents is used in calculating these accident measures. However, since the accident population involves many accidents that are not correctable by road improvements, the
locations identified by this method may not be truly hazardous or accident prone from a road environment perspective. There are three components of the highway system: the driver, the vehicle and the road environment. Accidents occur due to a failure in any of these components or a combination of them as shown in Figure 3.1.

Therefore, the identification of accident prone locations should be based on the factors which contributed to their accidents. For example, accidents which occur due to adverse road design should have greater influence for highway departments in identifying accident prone locations than those which occur due to impaired driving. Unfortunately, finding a pattern of contributing factors is usually not a simple task due to their complex interaction. For example, if weather conditions are poor, drivers may drive more cautiously. If a highway is improved to a higher standard, drivers may drive faster or less cautiously than before the improvement took place, and so forth.

### 3.2.1 The Need for a New Method

Most of the recent accident research has focused on enhancing the statistical tools to predict accident occurrence and identify accident prone locations (Wright, 1988; Nicholson, 1991; and Hauer, 1992). Less attention has been given to the "causes" or contributing factors of accidents and the understanding of their patterns. The lack of focus on studying accident causes in the literature can be attributed to the lack of an adequate tool for the analysis of accident data. The only attempts found in the literature
Figure 3.1 Classification of accidents according to causes
that focused on accident causes (Sabey and Taylor, 1980; and Treat, 1980) were aimed at studying factors associated with accidents. No suggestion was given about how to incorporate the results in highway safety improvement programs. Furthermore, these studies were based on detailed post accident investigations by human experts that involved site visits and interviewing the victims. These efforts, while more accurate than any computational method, are not useful for the purpose of identifying accident prone locations on a system-wide basis. What is needed is a computerized algorithm that is efficient in analyzing large scale accident databases in the form and quality of what exists.

The modified black spot program identifies accident prone locations based on the assessment of accident contributing factors. The basic idea is to classify accidents according to their patterns and contributing factors into one of the three components of the highway system or a combination of these components. Accidents that do not belong to the road environment component are excluded from the identification of accident prone locations. The method uses fuzzy pattern recognition techniques for the classification process. There are several traditional methods for classification analysis either explicit such as discriminant functions and nearest prototype rules; or implicit such as $K$-nearest neighbor rules. However, these methods do not suit the purpose of this work for two reasons. First, the relationships between accidents and the variables associated with them have a complex interaction and are of uncertain nature. Secondly, in the traditional methods, observations (accidents) can belong to one and only one group (cluster), while in this case the same accident can belong to more than one group with different degrees. Fuzzy set theory can effectively handle the uncertainty and the information deficiencies due to the nature of accident data, as well as the complex interaction between its
variables. For these two reasons, fuzzy pattern recognition techniques are adopted for the classification process.

3.2.2 Fuzzy Sets and Membership Functions

In the classical set theory there is a distinct difference between elements that belong to a set and those that do not. The set boundaries are very sharp; an element is either a full member of the set or a non-member. However, most of the sets encountered in the physical real world do not have a precise defined criteria of membership. For example, it will be hard to define a precise membership criteria for the set "young men" or the set "long streets", etc. Elements of these sets need not to be either a full or non-member of the set; they can be of intermediate grade of membership.

The theory of fuzzy sets was introduced by Zadeh (1965). It is based on the simple idea of introducing a degree of belonging of an element with respect to some set. The theory deals with a subset $A$ of the universe of discourse $U$, where the transition between membership and non-membership is gradual rather than sharp. The degree of membership is specified by a number between 0 (full non-membership) and one (full membership). A fuzzy set $A$ of a universe of discourse $U$ is characterized by a membership function $u_A(x)$, which assigns to each element $x \in U$ a membership $u_A(x)$, in the interval $[0,1]$, that represents the grade of membership in $A$, i.e.:

$$A=((x, u_A(x)), x \in U)$$

(3.1)

The more an object $x$ belongs to $A$, the closer to 1 its grade of membership $u_A(x)$. 
3.2.3 Fuzzy Pattern Recognition

There are many definitions to the term "pattern recognition" following different schools of thought. However, pattern recognition can be generally defined as the search for structures in data (Bezdek, 1981). The main components of pattern recognition are cluster analysis, and classification analysis. Cluster analysis refers to the process of partitioning a finite data set $X$ of objects into a certain number ($c$) of natural and homogeneous subsets (clusters). The elements of the same cluster are as similar as possible to each other and as different as possible to elements in other clusters. The number of clusters are usually predefined (fixed) or may result from physical or mathematical constraints to the problem (Bezdek and Pal, 1992). A similarity criterion has to be defined to base the clustering on. In this process, no prior information is available on the structures of the data, and thus the output of the process may or may not produce meaningful clusters. Sneath and Sokal (1973) observe: "Cluster methods will yield clusters of some kind, whatever the structure of the data, even if the distributions are random". This is why the process of clustering analysis is usually referred to as "unsupervised learning". The results of the process is greatly influenced by the choice of both the number of clusters ($c$) and the similarity criteria.

Classification analysis, on the other hand, uses prior information in the form of labeled data (data of known classification) to establish a classifier function. After the classifier function is defined, it should be capable of classifying every data object in the entire space. In other words classification analysis is a "supervised learning" process, which is undertaken to differentiate between classes (clusters) formed on a priori basis. The problem in classification analysis is not to discover classes but to identify a set of characteristics that can significantly differentiate between classes.
The advantage of using fuzzy sets is that the degree of membership in a set can be specified rather than the binary "yes or no" membership in the classical set theory. This is very important in pattern recognition where the membership of an element in a certain group is usually not clear. The relation between fuzzy sets and classification is that given an object $p$ and a cluster $C$, the basic question is not whether $p$ is a member of $C$, but the degree to which $p$ belongs to $C$, i.e. grade of membership of $p$ in $C$ (Kandel, 1982). Crisp techniques of pattern recognition will assign an element to only one group, while in fuzzy pattern recognition an observation can belong to more than one group with different degrees. There are many classification algorithms that utilize fuzzy set theory. These algorithms can roughly be categorized in three groups:

1) Those based on using fuzzy relations and the theory of approximate reasoning (e.g. Nath and Lee, 1983);

2) Those utilizing fuzzy decision trees (e.g. Chang and Pavlids, 1977); and

3) Those based on modifying classical algorithms such as the $K$-Nearest Neighbor ($K$-NN) and the nearest prototype algorithms (e.g. Keller et al., 1985).

Given a set of sample observations $\{x_1, \ldots, x_n\}$, a fuzzy $c$ partition of these observations specifies the degree of membership of each observation in each of the $c$ classes. The partition can be denoted by the $n \times c$ matrix $U$, where $u_{ik}$ is the degree of membership of the $k$th observation in the $i$th class. For $i=1, \ldots, c$, and $k=1, \ldots, n$, the following properties must be true for $U$ to be a fuzzy $c$ partition (Keller et al., 1985):

$$\sum_{i=1}^{c} u_{ik} = 1, \quad (3.2)$$
\[ 0 < \sum_{i=1}^{n} u_{ik} < n, \]  

(3.3)

\[ u_{ik} \in [0,1]. \]  

(3.4)

Equation 3.2 represents the additivity condition which ensures that the sum of the membership values for each observation in the \( c \) classes is one. This condition is suitable for the case where the source of information is considered to have perfect credibility. Obviously, relaxing this condition is desirable in order to have a better match with real situations. Sugeno (1974) suggested using the concept of fuzzy measures, another mathematical expression of fuzziness in contrast to fuzzy sets. A fuzzy measure on \( X \) is characterized by assigning the grade of certainty of "\( x \in A \)" to each subset \( A \) of \( X \), where \( x \) is an unknown element of \( X \). The advantage of using this concept is that it allows for non-additivity leading to more flexibility and better applicability to ambiguous circumstances.

### 3.2.4 Selection of the Algorithm

There are often two conflicting criteria in the selection of classification algorithms: low error rates, and minimum computation time to reduce cost. However, given that the objective of this application is to classify all objects in a very large database, it was considered that algorithms which require large computational resources (mainframe CPU time) are not feasible for this application. Consequently, the majority of the algorithms mentioned in Section 3.2.2, including those utilizing Sugeno's fuzzy measures concept, could not be utilized. It was finally decided to use the fuzzy K-NN algorithm since this algorithm best suited the application. It is simple and easy to implement, less computationally intensive, and is considered one of the most accurate algorithms in
pattern recognition (Keller et al., 1985; Bezdek et al., 1986; and Jousselin and Dubuisson, 1987).

3.2.5 Conceptual Basis of the Algorithm

The algorithm assesses the degree with which each accident belongs to the three highway system components; the driver, the vehicle and the road environment. The classification method uses a fuzzy version of the crisp $K$-Nearest Neighbor algorithm ($K$-NN). The basic idea behind the $K$-Nearest Neighbor rules is that samples which fall close together in feature space are likely to belong to the same class. The classical (crisp) $K$-NN algorithm classification rule assigns an input sample vector $y$, which is of unknown classification, to the class (group) which is represented by a majority amongst its $K$-nearest neighbors (Duda and Hart, 1973). If a tie between two classes occurred, the vector is assigned to the class, of these classes who tied, for which the sum of distances from the vector to each neighbor in the class is minimum. The $K$-nearest neighbors are chosen from a labeled data sample (data of known classification). Figure 3.2 illustrates the $K$-NN rule for two classes in a two-dimensional measurement space.
The Detection Phase: A Modified Black Spot Program

The detection phase involves classifying plant samples to determine if they are infected with black spot disease. The process includes

taking sample points from different classes of plants.

• Sample point from class I
• Sample point from class II
• A point with unknown classification

Figure 3.2 The K-NN Rule for Two Classes in a Two-Dimensional Sample Space

The K-nearest neighbors boundary separates the two classes. The K-NN rule would associate this point with class I.
Let \( W = \{x_1, x_2, \ldots, x_n\} \) be a set of \( n \) labeled samples, the algorithm can be described as follows (Duda and Hart, 1973):

**BEGIN**

Input \( y \), of unknown classification.
Set \( K, 1 \leq K \leq n \).
Initiate \( i = 1 \).
DO UNTIL (K-nearest neighbors found)
     Compute distance from \( y \) to \( x_i \).
     IF \( (i \leq K) \) THEN
          Include \( x_i \) in the set of K-nearest neighbors
     ELSE IF \( (x_i \) is closer to \( y \) than any previous nearest neighbor) THEN
          Delete farthest in the set of K-nearest neighbors.
          Include \( x_i \) in the set of K-nearest neighbors
     END IF
     Increment \( i \).
END DO UNTIL
Determine the majority class represented in the set of K-nearest neighbors.
IF (a tie exists) THEN
     Compute sum of distances of neighbors in each class which tied.
     IF (no tie occurs) THEN
          Classify \( y \) in the class of minimum sum of distances
     ELSE
          Classify \( y \) in the class of last minimum sum of distances found
     END IF
ELSE
     Classify \( y \) in the majority class.
END IF
END
3.2.6 The Fuzzy $K$-Nearest Neighbors Algorithm

The fuzzy $K$-nearest neighbors algorithm assigns class membership to a sample observation rather than assigning the observation to a certain class as in the case of the classical algorithm. The membership values are assigned based on the observation distance from its $K$-nearest neighbors and their memberships (Keller et al., 1985).

If $W = \{x_1, \ldots, x_n\}$ is the set of $n$ labeled samples and $u_j$ is the membership of the $j$th labeled data in the $i$th class, then the fuzzy $K$-NN algorithm is simply described as follows (Keller et al., 1985):

\begin{align*}
\text{BEGIN} \\
\text{Input } y, \text{ of unknown classification.} \\
\text{Set } K, 1 \leq K \leq n. \\
\text{Initialize } i = 1. \\
\text{DO UNTIL (} K \text{-nearest neighbors found) } \\
\quad \text{Compute distance from } y \text{ to } x_i. \\
\quad \text{IF } (i \leq K) \text{ THEN} \\
\quad \quad \text{Include } x_i \text{ in the set of } K \text{-nearest neighbors} \\
\quad \text{ELSE IF } (x_i \text{ is closer to } y \text{ than any previous nearest neighbor}) \text{ THEN} \\
\quad \quad \text{Delete farthest in the set of } K \text{-nearest neighbors.} \\
\quad \quad \text{Include } x_i \text{ in the set of } K \text{-nearest neighbors} \\
\quad \text{END IF} \\
\quad \text{Increment } i. \\
\text{END DO UNTIL} \\
\text{Initialize } i = 1 \\
\text{DO UNTIL } (y \text{ assigned membership in all classes}) \\
\quad \text{Compute } u_i(y) = \frac{\sum_{j=1}^{K} u_j \left(1 / \left\| y - x_j \right\|^{2/(m-1)}\right)}{\sum_{j=1}^{K} \left(1 / \left\| y - x_j \right\|^{2/(m-1)}\right)} \quad (3.5) 
\end{align*}
Increment \( i \).

END DO UNTIL

END

As shown in Equation 3.5, the assigned memberships of observations are influenced by the class memberships of the \( K \)-nearest neighbors \( u_i \) and the inverse of the distance to the \( K \)-nearest neighbors. The best value of the integer \( K \) is usually data dependent. \( K \) has to be smaller than the sample size \( n \), but not so small to affect the accuracy of classification. The accuracy of the classification process usually increases with \( K \) up to a certain limit where it begins to decrease as \( K \) increases. The memberships of the labeled sample can be assigned in several ways such as using fuzzy cluster analysis or based on expert opinions. The distance between observations can be represented by any distance measure such as the Euclidean distance, defined as (Bezdek, 1981):

\[
d^2_{xy} = \sum_{v=1}^{p} (y_v - x_{iv})^2 = (y_i - x_i)'(y_i - x_i) \quad (3.6)
\]

where \( p \) is the number of variables for observation \( i \). With this distance, the variables are given equal weights. Another form of distance measure is the Mahalanobis' distance in which the correlation between variables are taken into account (Bezdek, 1981):

\[
d^2_{xy} = (y_i - x_i)'\Sigma^{-1}(y_i - x_i) \quad (3.7)
\]

where \( \Sigma \) is the sample covariance matrix of \( x \). The Euclidean distance is usually used when the variables are statistically independent, while the Mahalanobis' distance mitigates the effects of statistical dependence between pairs of variables.

The variable \( m \) in Equation (3.5) defines how heavily the distance is weighted when calculating each neighbor's contribution to the membership value (Keller et al., 1985). When \( m=2 \), the contribution of neighbors is weighted by the reciprocal of its distance.
from the point being classified. As \( m \) increases the contribution of each neighbor is more evenly weighted. Usually, practitioners use \( m = 2 \).

3.2.7 Application of the Method

To demonstrate the applicability of the fuzzy pattern recognition technique to the identification of the accident prone locations, the above algorithm was run on a sample data set. The initial implementation of the algorithm used C++ on a PC computer. The algorithm was then implemented on the BCSYSTEM mainframe computer using PL1 (Appendix B).

3.2.7.1 The Accident Data

The data came from the provincial accident database files consisting of all police reported accidents in the Province of British Columbia. The sample data set contained 7000 accident records randomly selected between the years 1989 and 1992. The selected accidents were all attended by police personnel (as opposed to self reported accidents). An algorithm for filtering the data was created to check the records for any conflicting data. Also, accident records which had missing variables were excluded. A total of 45 variables were available in each accident record. The data was standardized using the following function (Romesburg, 1984):

\[
Z_{ij} = \frac{x_{ij} - c_{\min j}}{c_{\max j} - c_{\min j}}
\]  
(3.8)
where $c_{\text{max},j}$ and $c_{\text{min},j}$ are the maximum and minimum of the $j$th variable in all observations. The main reason for standardizing the data matrix is that the variables are usually measured in different units. By standardizing the variables and recasting them in dimensionless units, the arbitrary effects of similarities between objects are removed.

### 3.2.7.2 The Selected Variables

After carefully reviewing the variables available in each accident record, 14 variables were selected for further analysis. Another variable, not included in accident records, which represents the traffic volume to capacity ratio was also added. Only variables that appeared most useful in describing accident patterns were selected. The selected variables included a variety of accident and road characteristics as shown in Table 3.1.

In addition to the variables listed in Table 3.1, another six variables describing accident contributing factors, as assigned by the police officers investigating the accident, were also included. The first three contributing factors were associated with the first vehicle in the crash and the other three with the second vehicle (for multi-vehicle accidents). The contributing factors ranged from driver related; such as alcohol involvement, and driving without due care, to vehicle related; such as engine or brake failure, to road related; such as road obstructions and pavement surface deficiencies. A full description of these factors is given in Table 3.2.
### Table 3.1. Selected Variables and Their Levels

<table>
<thead>
<tr>
<th>Variable</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Degree of curvature</td>
<td>1. Straight</td>
</tr>
<tr>
<td></td>
<td>2. Single Curve</td>
</tr>
<tr>
<td></td>
<td>3. Sharp Curve</td>
</tr>
<tr>
<td>2. Road grade</td>
<td>1. Flat</td>
</tr>
<tr>
<td></td>
<td>2. Some grade</td>
</tr>
<tr>
<td></td>
<td>3. Steep grade</td>
</tr>
<tr>
<td></td>
<td>4. Hillcrest/sag</td>
</tr>
<tr>
<td>3. Speed limit</td>
<td>1. 50-60 kph</td>
</tr>
<tr>
<td></td>
<td>2. 70-80 kph</td>
</tr>
<tr>
<td></td>
<td>3. 90-110 kph</td>
</tr>
<tr>
<td>4. Surface condition</td>
<td>1. Dry</td>
</tr>
<tr>
<td></td>
<td>2. Wet</td>
</tr>
<tr>
<td></td>
<td>3. Ice/snow</td>
</tr>
<tr>
<td>5. Weather condition</td>
<td>1. Clear/Cloudy</td>
</tr>
<tr>
<td></td>
<td>2. Raining</td>
</tr>
<tr>
<td></td>
<td>3. Smog/Fog</td>
</tr>
<tr>
<td></td>
<td>4. Ice/Snow</td>
</tr>
<tr>
<td>6. Lighting conditions</td>
<td>1. Day light</td>
</tr>
<tr>
<td></td>
<td>2. Dark/Full illumination</td>
</tr>
<tr>
<td></td>
<td>3. Dark/Some illumination</td>
</tr>
<tr>
<td></td>
<td>4. Dark/No illumination</td>
</tr>
</tbody>
</table>
Table 3.1. Selected Variables and Their Levels (Cont.)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>7. Land use</td>
<td>1. Undeveloped/agriculture Area</td>
</tr>
<tr>
<td></td>
<td>2. Rural residential area</td>
</tr>
<tr>
<td></td>
<td>3. Urban residential</td>
</tr>
<tr>
<td></td>
<td>4. Central Business District</td>
</tr>
<tr>
<td>8. Accident time</td>
<td>1. Non-rush hour</td>
</tr>
<tr>
<td></td>
<td>2. Rush hour</td>
</tr>
<tr>
<td>9. Accident location</td>
<td>1. At intersection</td>
</tr>
<tr>
<td></td>
<td>2. Not at intersection</td>
</tr>
<tr>
<td>10. Accident type</td>
<td>1. Single vehicle-fixed object</td>
</tr>
<tr>
<td></td>
<td>2. Single vehicle-other</td>
</tr>
<tr>
<td></td>
<td>3. Multiple vehicle-head on</td>
</tr>
<tr>
<td></td>
<td>4. Multiple vehicle-side/angle</td>
</tr>
<tr>
<td></td>
<td>5. Multiple vehicle-rear-end</td>
</tr>
<tr>
<td></td>
<td>6. Pedestrian</td>
</tr>
<tr>
<td></td>
<td>7. Animal</td>
</tr>
<tr>
<td>11. Severity</td>
<td>1. Property damage only</td>
</tr>
<tr>
<td></td>
<td>2. Injury</td>
</tr>
<tr>
<td></td>
<td>3. Fatal</td>
</tr>
<tr>
<td>12. Traffic control device</td>
<td>1. Exist</td>
</tr>
<tr>
<td></td>
<td>2. None</td>
</tr>
</tbody>
</table>
Table 3.1. Selected Variables and Their Levels (Cont.)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Levels</th>
</tr>
</thead>
</table>
| 13. Use of a restraint device | 1. Device used  
2. Vehicle equipped but device not used  
3. Vehicle not equipped |
| 14. Volume/capacity ratio | - Value                                           |
| 15. Vehicle type          | 1. Passenger cars only  
2. At least one van or pickup  
3. At least one truck or bus |
Table 3.2. Apparent Contributing Factors to Accidents

<table>
<thead>
<tr>
<th>1. Alcohol involvement</th>
<th>20. Cutting in</th>
<th>63. Headlights defective</th>
</tr>
</thead>
<tbody>
<tr>
<td>2. Driver inexperience</td>
<td>21. Driving on wrong side of road</td>
<td>64. Turn Signal defective</td>
</tr>
<tr>
<td>3. Drugs</td>
<td>22. Improper turning</td>
<td>65. Oversize vehicle</td>
</tr>
<tr>
<td>4. Extreme fatigue</td>
<td>23. Failing to yield right of way</td>
<td>66. Steering failure</td>
</tr>
<tr>
<td>5. Fell asleep</td>
<td>24. Ignoring traffic control device</td>
<td>67. Tires failure inadequate</td>
</tr>
<tr>
<td>6. Illness</td>
<td>25. Pedestrian error confusion</td>
<td>68. Two hitch failure</td>
</tr>
<tr>
<td>7. Sudden loss of consciousness</td>
<td>40. Obstruction on road</td>
<td>69. Driverless vehicle</td>
</tr>
<tr>
<td>8. Pre-existing physical disability</td>
<td>41. pavement surface defective</td>
<td>70. Windshield defective</td>
</tr>
<tr>
<td>9. Prescribed medication</td>
<td>42. Road maintenance/construction</td>
<td>71. Engine failure</td>
</tr>
<tr>
<td>10. Attempted suicide</td>
<td>43. Sign obstruction</td>
<td>72. Suspension defect</td>
</tr>
<tr>
<td>11. Driving without due care</td>
<td>44. Insufficient traffic control</td>
<td>73. Restraint system</td>
</tr>
<tr>
<td>12. Failing to signal</td>
<td>45. Road/intersection design</td>
<td>74. Insecure load</td>
</tr>
<tr>
<td>13. Ignoring officer</td>
<td>46. Roadside/hazard</td>
<td>75. Dangerous good</td>
</tr>
<tr>
<td>14. Previous traffic accident</td>
<td>47. Wild animal</td>
<td>76. Vehicle modification</td>
</tr>
<tr>
<td>15. Following too closely</td>
<td>48. Weather</td>
<td>77. Glare artificial</td>
</tr>
<tr>
<td>16. Improper passing</td>
<td>49. Visibility impaired</td>
<td>78. Glare sunlight</td>
</tr>
<tr>
<td>17. Unsafe speed</td>
<td>60. Accelerator defective</td>
<td>79. Domestic animal</td>
</tr>
</tbody>
</table>

60
3.2.8 Validation of the Algorithm

The Fuzzy K-NN algorithm was applied to three randomly chosen sets of unlabeled data each containing 300 accidents. The labeled data consisted of 600 accidents. The membership values of the labeled data in the three classes were assigned by two safety experts in the Ministry after examining the accident records and the apparent contributing factors (supplied by the police officers attending the accident scene). Every effort was made during the selection of the labeled accident data to cover as many different accident types as possible. Membership values were also assigned to the three sets of the unlabeled data to validate the results.

3.2.8.1 Test for Consistency Among Experts

The use of more than one expert may introduce a problem of consistency, or in other words, would experts agree among themselves?. The statistic kappa (Cohen, 1960; Fleiss, 1971; Spring, 1993) was employed to measure the degree of agreement between the two experts. Using the membership values assigned by both experts, accidents were classified into one of the seven categories shown in Figure 3.3. The agreement and disagreement between the two experts on data set 1 (300 observations each) are shown in Tables 3.3. As shown in the table, the number of accidents assigned by both experts to category 1 is 155, the number of accidents assigned by the first expert to category 1 and by the second expert to category 5 is 30 and so on. The kappa statistic is defined as:
The Detection Phase: A Modified Black Spot Program

Figure 3.3 Classification regions

Road Environment Related Factors
(3)

(5)

Driver Related Factors
(1)

(7)

(4)

Vehicle Related Factors
(2)

(6)
\[ \kappa = \frac{P - P_e}{1 - P_e} \]  

(3.9)

where:

- $P$ is the overall percent agreement;
- $P_e$ is the overall percent agreement expected by chance.

A positive value for $\kappa$ indicates agreement, a value of zero indicates an agreement that can be expected by chance, and a negative value indicates disagreement. For the data in Table 3.3, $P$ is calculated by the sum along the diagonal divided by the total number of cases. Thus, $P = \frac{226}{300} = 0.753$. The overall percent agreement expected by chance may be calculated from the percentage of assignment of each expert to the seven categories, i.e.

\[
P_e = \frac{177}{300} \times \frac{190}{300} + \frac{7}{300} \times \frac{8}{300} + \frac{9}{300} \times \frac{12}{300} + \frac{7}{300} \times \frac{86}{300} + \frac{5}{300} \times \frac{5}{300} \]

= 0.45

(3.10)

Therefore, using Equation 3.9, $\kappa = 0.552$.

The variance of $\kappa$ is calculated using (Fleiss, 1971):

\[
\text{Var}(\kappa) = \frac{1}{N} \times \frac{\sum p_j^2 - (\sum p_j^2)^2}{(1 - \sum p_j^2)^2}
\]

(3.11)

where:

- $N$ is the total number of cases;
- $j = 1, \ldots, k$ is the seven categories of classification;
The Detection Phase: A Modified Black Spot Program

\( p_j \) is the proportion of all assignments of the jth category

For example, \( p_1 = 0.5 \left( \frac{190}{300} + \frac{177}{300} \right) = 0.611 \). And therefore, using Equation 3.11, \( \text{Var}(\kappa) = 0.0027 \).

Under the hypothesis of no agreement beyond chance and using the central limit theorem, the value \( \kappa / \sqrt{\text{Var}(\kappa)} \) may be approximately distributed as a standard normal variant (Fleiss, 1971). Therefore, \( \kappa / \sqrt{\text{Var}(\kappa)} = \frac{5.52}{\sqrt{0.0027}} = 10.62 \), which greatly exceeds the critical Z value of 2.32 at the 99% significance level, indicating strong agreement between the two experts. The values of \( \kappa / \sqrt{\text{Var}(\kappa)} \) for data sets 2 and 3 were 9.80 and 8.51 respectively which also indicate strong general agreement between the two experts.

Table 3.3 also shows that all classification disagreements between the two experts where at the boundaries between classes (categories 4, 5, 6 and 7). No disagreement occurred at categories 1, 2 and 3 which further indicates consistency between the two experts.

3.2.8.2 Comparison Between Experts and the Algorithm

To examine the results produced by the algorithm, a comparison between the results of the algorithm and the expert classification of the unlabeled data was conducted. Accidents were assigned to one of the seven categories shown in Figure 3.3. An \( \alpha \)-cut operator of 0.15 was applied to the membership values (observations with memberships less than 0.15 in any class were assigned zero membership in that class). The \( \alpha \)-cut value of 0.15 was selected based on the minimum membership value (greater than zero) assigned by the two experts to any accident in the three classes. The \( \alpha \)-cut operator is only
Table 3.3. Agreement Between the Two Experts on Data Set 1

<table>
<thead>
<tr>
<th>Expert 1</th>
<th>Category 1</th>
<th>Category 2</th>
<th>Category 3</th>
<th>Category 4</th>
<th>Category 5</th>
<th>Category 6</th>
<th>Category 7</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
</tr>
<tr>
<td>Category 1</td>
<td>155</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>190</td>
</tr>
<tr>
<td>Category 2</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Category 3</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>Category 4</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>Category 5</td>
<td>20</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>51</td>
<td>0</td>
<td>1</td>
<td>76</td>
</tr>
<tr>
<td>Category 6</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Category 7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>177</strong></td>
<td><strong>7</strong></td>
<td><strong>9</strong></td>
<td><strong>12</strong></td>
<td><strong>86</strong></td>
<td><strong>4</strong></td>
<td><strong>5</strong></td>
<td><strong>300</strong></td>
</tr>
</tbody>
</table>

Category 1: all driver related factors
Category 2: all vehicle related factors
Category 3: all road environment related factors
Category 4: interaction between driver and vehicle related factors
Category 5: interaction between driver and road environment related factors
Category 6: interaction between vehicle and road environment related factors
Category 7: interaction between driver, vehicle and road environment related factors

65
used for the purpose of comparing the number of accidents classified by the experts and the algorithm in the seven categories. The actual membership values produced by the algorithm without the \( \alpha \)-cut will be used in the identification of accident prone locations as will be described in Section 3.2.9.1.

The number of the misclassified data observations (classified in a different region by the algorithm relative to expert classification) for different \( K \) values is given in Table 3.4.

Another measure of misclassification defined by the author as:

\[
E = \frac{\sum_{k=1}^{n} \left( \sum_{i=1}^{c} (u_{ik} - u_{ik}')^2 \right)^{0.5}}{n}
\]

(3.12)

where:

- \( E \) is a measure of classification error,
- \( c \) is the number of classes (3 in this case),
- \( n \) is the number of data observations per sample,
- \( u_{ik} \) is the membership value of the \( k \)th observation in the \( i \)th class as assigned by the experts and
- \( u_{ik}' \) is the membership value of the \( k \)th observation in the \( i \)th class as estimated by the algorithm.

A value of \( E \) equal to zero indicates identical experts and algorithm membership values, while a value of 1.41 indicates a complete disagreement. On average, about 85% of the data classification agreed with those of the experts. All misclassifications occurred at the boundaries between classes. No misclassifications occurred among regions 1, 2 and 3 (all driver related factors, all vehicle related factors, all road environment related factors). The results were relatively not sensitive to the choice of \( K \) values up to \( K=50 \), which is desirable. The \( E \) value averaged about 0.15 which indicates a good level of confidence in the results. These results indicate that the algorithm provides a good systematic approach for the classification of accidents into a finite set of broad causes.
## Table 3.4 Number of Misclassified Observations

<table>
<thead>
<tr>
<th>K</th>
<th>Data set 1 (n=300)</th>
<th>Data set 2 (n=300)</th>
<th>Data set 3 (n=300)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Misclassified</td>
<td>Misclassified</td>
<td>Misclassified</td>
</tr>
<tr>
<td></td>
<td>observations</td>
<td>observations</td>
<td>observations</td>
</tr>
<tr>
<td>10</td>
<td>44</td>
<td>51</td>
<td>57</td>
</tr>
<tr>
<td></td>
<td>0.113</td>
<td>0.142</td>
<td>0.157</td>
</tr>
<tr>
<td>15</td>
<td>46</td>
<td>54</td>
<td>58</td>
</tr>
<tr>
<td></td>
<td>0.118</td>
<td>0.151</td>
<td>0.160</td>
</tr>
<tr>
<td>25</td>
<td>44</td>
<td>54</td>
<td>56</td>
</tr>
<tr>
<td></td>
<td>0.112</td>
<td>0.154</td>
<td>0.157</td>
</tr>
<tr>
<td>50</td>
<td>41</td>
<td>63</td>
<td>54</td>
</tr>
<tr>
<td></td>
<td>0.110</td>
<td>0.181</td>
<td>0.152</td>
</tr>
<tr>
<td>100</td>
<td>49</td>
<td>71</td>
<td>63</td>
</tr>
<tr>
<td></td>
<td>0.130</td>
<td>0.21</td>
<td>0.172</td>
</tr>
</tbody>
</table>
3.2.8.3 Comparison with Previous Studies

As mentioned earlier, there are two studies which were performed to identify factors associated with a large sample of accidents. The first study was performed in the US by Indiana University and is usually referred to as the Tri-Level Study (Treat, 1980). The second study was performed in the UK by the Transport and Road Research Laboratory (Sabey and Taylor, 1980). Both studies were performed by a team of multidisciplinary experts. The studies involved site visits, mechanical inspection of the vehicles involved and interviews with the victims. The two studies' results were summarized by Rumar (1985) in Figure 3.4. As shown in this figure, the results of the two studies seem consistent. The UK study concluded that driver related factors are the sole contributors to 65% of accidents compared to 57% in the US study. About 95% of all accidents involved some driver related factors in the UK study compared to 94% in the US study. Road environment and vehicle related factors were rarely the sole contributing factors to accidents in both studies. Road environment related factors were present as contributory or sole factors in 24% of accidents in the UK study and 27% in the US study.

The results obtained from the expert classification and the algorithm results for this study are given in Figure 3.5. The sample contained a total of 900 accidents (the three data sets of 300 each). The experts and algorithm results are remarkably consistent with one another and with those of the US and the UK studies. Again, the majority of accidents (about 96%) involved some driver related factors. Experts' classification suggested that about 28% of accidents involved some road related factors compared with 24% in the algorithm results.
Figure 3.4 Percent contribution to accidents as obtained in UK and US studies. Source: Rumar (1985)
The Detection Phase: A Modified Black Spot Program

Figure 3.5 Percent Contribution to Accidents as Obtained from Experts and Algorithm

<table>
<thead>
<tr>
<th>Road Environment</th>
<th>Road User</th>
<th>Vehicle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single factor</td>
<td>Double factor</td>
<td>Treble factor</td>
</tr>
<tr>
<td>3/1</td>
<td>62/3</td>
<td>3/3</td>
</tr>
<tr>
<td>25/24</td>
<td>5/3</td>
<td></td>
</tr>
<tr>
<td>1/1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1/0</td>
<td></td>
</tr>
</tbody>
</table>

Total percentage for each factor (overlapping)

30/26        93/96        10/7

70
3.2.9 Applications of the Algorithm to the Identification of APLs in B.C.

An accident prone location means different things to different analysts. A highway section which exhibits a significant number of accidents due to speeding or impaired driving may be an accident prone location on the enforcement agency's (police) list. On the other hand, a highway section that exhibits a significant number of accidents due to hitting a roadside fixed object may be an accident prone location on a highway agency's list. In reality, however, accidents can rarely be attributed to a single driver, vehicle, or road related cause. Instead, accidents occur, in most cases, as a result of failure in more than one element of the highway system. The challenge then is to utilize the available data to classify accidents into a finite set of categories as in Figure 3.2. Once accidents have been classified into separate categories, trends or patterns become much easier to find and countermeasures can be developed.

The results of the fuzzy pattern recognition algorithm were used to modify the traditional black spot identification of APLs. The method was labeled "modified black spot". The primary difference between the modified black spot program and traditional black spot programs lies in the identification of accident prone locations. In traditional black spot programs, locations are identified as accident prone if they exhibit a significant number of accidents above an established norm. In the modified black spot program, locations must exhibit a significant number of correctable (i.e., road-related) accidents in order to be identified as accident prone.

Therefore, it is expected that the addition of the accident correctability criterion to the identification of accident prone locations in black spot programs will result in the following:
The Detection Phase: A Modified Black Spot Program

1. Reduce the total number of accident prone locations:

   If only road-related accidents are considered, then a significant number of accidents will be eliminated (or, given little weight) in calculating accident rates. Consequently, a fewer number of accident prone locations will be identified.

2. Alter the ranking of accident prone locations:

   Accident prone locations are normally ranked by the degree with which they exceed the typical accident rate. This ranking is crucial as it indicates the degree of proneness of locations to accidents. For example, the first of the top 20 accident prone locations in the traditional method, may be ranked 10th in the modified method, and the 15th may be ranked 4th, and so on. This is significant when road agencies can afford to examine only a limited number of accident prone locations. In some cases, the modified method can eliminate some of the top ranking accident prone locations in the traditional method from the accident prone location list. That is, significant efforts can be saved in trying to identify problems and determine solutions for locations which may not be correctable from a road point of view.

3.2.9.1 Redefining Accident Frequency and Rate

The identification of accident prone locations involves a comparison of a certain accident measure (usually, accident rate) with an established norm. Traditionally, the total number of accidents is used to calculate this accident measure. The algorithm proposed here will be used to modify the method of calculating accident measures. The new method screens accidents according to their relevance to the road, driver, and vehicle components. In
doing so, the algorithm calculates three values (one representing each component) and assigns them to each accident. Each value ranges between zero and one. For example, from a road improvement (engineering countermeasures) point of view, accident frequency and rate are calculated as:

\[
\text{Correctable Accident Frequency} = \frac{\sum_{i=1}^{n} W_i}{n}
\]

\[
\text{Correctable Accident Rate} = \frac{\sum_{i=1}^{n} W_i}{\text{Exposure Measure}}
\]

where

\( W_i \) = the degree with which the \( i \)th accident belongs to the road environment group without applying the \( \alpha \) cut operator,

\( n \) = the total number of accidents at the site during a certain time period, and

\text{Exposure} is usually measured in million vehicle kilometers for road sections and million entering vehicles for road intersections.

Various accident measures can be calculated according to the purpose of the agency analyzing the accident data. For example, from an enforcement agency's point of view, the degree with which accidents belongs to the road user group will be used instead of those of the road environment group in Equations 3.13 and 3.14.
3.2.9.2 The Identification Method

The Empirical Bayes procedure (Higle and Witkowski, 1988) described in Chapter 2, was adopted to identify accident prone locations. However, some modifications were made to the procedure as follows:

1. Identify appropriate reference groups that refer to distinct location categories and then aggregate the accident statistics for each reference group to get a gross estimation of the probability distribution of the accident rates across the reference group $f_R(\lambda)$. Examples of the criteria that can be used to establish these groups are:
   - location type (section/intersection),
   - type of intersection control (Signalized, Stop, Yield, etc.)
   - highway class (two lane, multi lane, freeway, etc.)

The identification of these reference groups is very important since different location types vary considerably in their accident patterns and characteristics. The aggregation of all locations into a single "regional-wide" group irrespective of any reference groups can lead to miss-identification of APLs as indicated by Abdelwahab and Sayed (1993).

2. Higle and Witkowski used Equation 2.24 to calculate whether a location is accident prone compared to specific confidence level, $\delta$. This gives no indication of the degree with which a location deviates from its expected accident rate. This deviation is very important since it represents the degree of proneness of a certain location. To overcome this problem, a critical accident
rate of each location, $\lambda_i$, which corresponds to a $\delta$ probability that the location accident rate $\tilde{\lambda}_i$ exceeds the reference group accident rate, $X_R$, was calculated by solving the following equation (a modification of Equation 2.24) for $\lambda_i$:

\[
\left[ 1 - \int_0^\infty \frac{\beta_i^{a_i} \Gamma(a_i)}{\Gamma(\alpha_i)} \lambda_i^{a_i-1} e^{-\beta_i \lambda_i} d\lambda \right] = \delta
\]

(3.15)

where $\delta$ was considered to be 0.99.

The ratio of the observed accident rate, $\tilde{\lambda}_i$, to the critical rate calculated from Equation 3.15 can represent the proneness of the location. If this value is less than one, the location is not considered accident prone. For values greater than one, the higher this value, the higher the degree of accident proneness.

While there is no problem with the application of the Empirical Bayes procedure to traditional accident rates, there are some difficulties with its application to correctable accident rates. The problem is whether the assumption of a gamma distribution for correctable accident rates is valid. The difficulty with estimating the actual distribution for the correctable rates results from the lack of knowledge about the distribution of $W_i$, in particular because less is known about the contribution of the three highway components (driver, road, vehicle) to the randomness in accident occurrence. To check the effect of this assumption, correctable accident rate observations in four location categories: signalized intersections, two lane sections, multi-lane sections, and freeway sections were fitted to the gamma distribution. The accident data came from the South Coast Region of the province of British Columbia as will be described in the next Section. The goodness-of-fit test, as shown in Figures 3.6 to 3.9, indicated that correctable accident rates can be modeled satisfactory using a gamma distribution. A sample calculation is given in Table 3.5.
The Detection Phase: A Modified Black Spot Program

Figure 3.6 Correctable Accident Rates Fitted to a gamma Distribution for the Signalized Intersections Category

Correctable Accident rate (acc/mvk)

Figure 3.7 Correctable Accident Rates Fitted to a gamma Distribution for the Two-lanes Sections Category

Correctable Accident rate (acc/mvk)
Figure 3.8 Correctable accident Rates fitted to a gamma Distribution for the Multi-lane Sections Category

Figure 3.9 Correctable accident Rates fitted to a gamma Distribution for the Freeway Sections category
The Detection Phase: A Modified Black Spot Program

Table 3.5 Goodness-of-Fit Test for Correctable Accident Rates in the Signalized Intersections Category

<table>
<thead>
<tr>
<th>Lower Limit</th>
<th>Upper Limit</th>
<th>Observed Frequency</th>
<th>Expected Frequency</th>
<th>Chi-square</th>
</tr>
</thead>
<tbody>
<tr>
<td>at or below</td>
<td>0.0400</td>
<td>49</td>
<td>42.6</td>
<td>0.9716</td>
</tr>
<tr>
<td>0.0400</td>
<td>0.0800</td>
<td>39</td>
<td>38.8</td>
<td>0.0008</td>
</tr>
<tr>
<td>0.0800</td>
<td>0.1200</td>
<td>27</td>
<td>31.0</td>
<td>0.5095</td>
</tr>
<tr>
<td>0.1200</td>
<td>0.1600</td>
<td>21</td>
<td>24.0</td>
<td>0.3750</td>
</tr>
<tr>
<td>0.1600</td>
<td>0.2000</td>
<td>18</td>
<td>18.3</td>
<td>0.0063</td>
</tr>
<tr>
<td>0.2000</td>
<td>0.2400</td>
<td>15</td>
<td>13.9</td>
<td>0.0868</td>
</tr>
<tr>
<td>0.2400</td>
<td>0.2800</td>
<td>9</td>
<td>10.5</td>
<td>0.2090</td>
</tr>
<tr>
<td>0.2800</td>
<td>0.3200</td>
<td>10</td>
<td>7.9</td>
<td>0.5759</td>
</tr>
<tr>
<td>0.3200</td>
<td>0.3600</td>
<td>4</td>
<td>5.9</td>
<td>0.6088</td>
</tr>
<tr>
<td>0.3600</td>
<td>0.4400</td>
<td>9</td>
<td>7.7</td>
<td>0.2229</td>
</tr>
<tr>
<td>above</td>
<td>0.4400</td>
<td>9</td>
<td>9.5</td>
<td>0.0230</td>
</tr>
</tbody>
</table>

Chi-square = 3.59 with 8 d.f; \( \chi^2 (8, 0.95) = 15.5 > 3.59 \) O.K.
3.2.9.3 Examples

To illustrate the application of the modified black spot program, the method was applied to the South Coast Region of the Province of British Columbia. The South Coast Region is one of six regions into which the provincial highway system is divided. There are approximately 3000 kms of primary highways (two lanes, multi-lane, and freeways), and 217 signalized intersections in this region. Using police-provided accident data from 1989 to 1991, accident prone locations were identified by both the traditional black spot method and the modified method proposed in this thesis. Results from the two methods were compared and are presented below.

Figure 3.10 shows the results of applying the two methods to identify accident prone locations in the signalized intersection category. Similarly, Figures 3.11 to 3.13 show the same results for the two-lane, multi-lane, and freeway sections categories. Two graphs are shown for each category: a) using the traditional method, and b) using the modified method.

A number of observations can be made about Figures 3.10 to 3.13:

- The vertical scale representing the accident rate in each traditional method figure is at least double the scale of that in the modified method. This reduction in accident rate in the modified method is a direct result of replacing each accident with a weight between zero and one proportional to its road correctability. For example, an accident that counts as one in the traditional method may only count as 0.15 accident in the modified method (reduced by 85%), and so forth. Therefore, caution should be exercised in comparing the modified accident rates with any published traditional accident rates. For
signalized intersections, the average traditional accident rate is 0.75 acc/mev, whereas in the modified method, the average accident rate is only 0.13 acc/mev.

- As discussed above, and as a result of weighting accidents by their road correctability, the number of accident prone locations using the modified method was significantly reduced. The number of accident prone locations in the traditional and modified methods as shown in Figures 3.10-3.13 are summarized in Table 3.6.

- In addition to increasing the potential effectiveness of safety improvement projects, limiting the list of accident prone locations by the modified method eliminates the frustration of diagnosing the nature and causes of the problem at the identified accident prone locations. A traditional accident prone location is not guaranteed to exhibit a recognizable pattern of accidents for which a solution can be readily found. An accident prone location identified by the modified method, on the other hand, is guaranteed to show some pattern of accidents for which at least one predetermined countermeasure can be proposed.
Table 3.6 Number of Accident Prone Locations Using Traditional and Modified Methods

($\delta = 0.99$)

<table>
<thead>
<tr>
<th>Type of Facility</th>
<th>Traditional Method</th>
<th>Modified Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signalized Intersections</td>
<td>50</td>
<td>14</td>
</tr>
<tr>
<td>Two-Lane Sections</td>
<td>48</td>
<td>9</td>
</tr>
<tr>
<td>Multi-Lane Sections</td>
<td>57</td>
<td>8</td>
</tr>
<tr>
<td>Freeway Sections</td>
<td>47</td>
<td>8</td>
</tr>
<tr>
<td>Total</td>
<td>202</td>
<td>39</td>
</tr>
</tbody>
</table>
Figure 3.10 Accident Prone Locations for Signalized Intersections
Using Traditional and Modified Methods

A) Using Traditional Method

B) Using Modified Method
Figure 3.11 Accident Prone Locations for Multi-lane Sections Using Traditional and Modified Methods

A) Using Traditional Method

B) Using Modified Method

# APL = 48

# APL = 9
Figure 3.12 Accident Prone Locations for Two-lane Sections Using Traditional and Modified Methods

A) Using Traditional Method

B) Using Modified Method

# APL = 57

# APL = 8
Figure 3.13 Accident Prone Locations for Freeway Sections Using Traditional and Modified Methods

A) Using Traditional Method

B) Using Modified Method

# APL = 47

# APL = 7
• As indicated in the introduction to this section, the modified method not only reduces the total number of accident prone locations (as discussed above), but also alters their ranking. This is very important in situations when the road authority has resources to address only a limited number of black spots. It is important to focus on those with the highest potential of accident reduction given the road authorities mandate. It is logical that the more a location deviates from the typical (i.e., norm or average) accident rate, the higher the potential for accident reduction.

To illustrate this point, Table 3.7 shows a list of accident prone signalized intersections in the South Coast Region ranked by the traditional method (showing only the top 20 to economize on space). For comparison purposes, the corresponding ranking using the proposed (modified) is also given along with the difference between the two ranks. The criteria used for ranking accident prone locations is the ratio of observed accident rate to the critical accident rate. In the modified method, the observed accident rate was adjusted by the algorithm as explained in section 3.2.9.1.

The two methods seem to agree on the ranking of the most accident prone location (Scott Rd. and 88th Ave.). Otherwise, there seems to be disagreement among the two methods. For example, the intersection of Lougheed Highway and Westwood St. ranks as 6th by the Traditional method, and 12th by the Modified method. Therefore, if only the top 10 accident prone locations were to be considered by the road authority, this intersection would be included unnecessarily, whereas the intersection of Scott Rd. and 96th Ave. (ranking 11th in the Traditional method and 7th in the Modified method.) would be excluded unnecessarily.
Table 3.7 Accident Prone Intersections Using the Traditional Method

(showing top 20 only)

<table>
<thead>
<tr>
<th>Intersection Name</th>
<th>Traditional Rank</th>
<th>Modified Rank</th>
<th>Difference (Trad-Mod)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scott Rd. &amp; 88th Ave.</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>King George Hwy &amp; 88th Ave.</td>
<td>2</td>
<td>4</td>
<td>-2</td>
</tr>
<tr>
<td>Fraser Hwy &amp; 152nd St.</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Scott Rd. &amp; 80th Ave.</td>
<td>4</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Fraser Hwy &amp; 64th Ave.</td>
<td>5</td>
<td>6</td>
<td>-1</td>
</tr>
<tr>
<td>Lougheed Hwy &amp; Westwood St.</td>
<td>6</td>
<td>12</td>
<td>-6</td>
</tr>
<tr>
<td>King George Hwy &amp; Hwy #10</td>
<td>7</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>Lougheed Hwy &amp; King Edward Ave.</td>
<td>8</td>
<td>9</td>
<td>-1</td>
</tr>
<tr>
<td>Lougheed Hwy &amp; Dwedney Trunk Rd.</td>
<td>9</td>
<td>15**</td>
<td>-6</td>
</tr>
<tr>
<td>King George Hwy &amp; 64th Ave.</td>
<td>10</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>Scott Rd. &amp; 96th Ave.</td>
<td>11</td>
<td>7</td>
<td>4</td>
</tr>
<tr>
<td>Lougheed Hwy &amp; Harris Rd.</td>
<td>12</td>
<td>16**</td>
<td>-4</td>
</tr>
<tr>
<td>Lougheed Hwy &amp; 207th St.</td>
<td>13</td>
<td>14</td>
<td>-1</td>
</tr>
<tr>
<td>King George Hwy &amp; 80th Ave.</td>
<td>14</td>
<td>13</td>
<td>1</td>
</tr>
<tr>
<td>King George Hwy &amp; Newton Rd.</td>
<td>15</td>
<td>11</td>
<td>4</td>
</tr>
<tr>
<td>Fraser Hwy &amp; 200th St.</td>
<td>16</td>
<td>20**</td>
<td>-4</td>
</tr>
<tr>
<td>King George Hwy &amp; 96th Ave.</td>
<td>17</td>
<td>19**</td>
<td>-2</td>
</tr>
<tr>
<td>Scott Rd. &amp; 72nd Ave.</td>
<td>18</td>
<td>25**</td>
<td>-7</td>
</tr>
<tr>
<td>Barnet Hwy &amp; Dwedney Trunk Rd.</td>
<td>19</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>Fraser Hwy &amp; 140th St.</td>
<td>20</td>
<td>27**</td>
<td>-7</td>
</tr>
</tbody>
</table>

** indicates intersection is not accident prone by the modified method
The difference in rank between the two methods seems to increase as one approaches the bottom of the list. For example, the intersection of Barnet Hwy & Dwedney Trunk Rd. ranks 9 steps higher in the Modified method compared with the Traditional method. Another important point is that many of the intersections that ranked highly in the traditional method were not accident prone in the modified method. For example, Lougheed Hwy & Dwedney Trunk Rd. intersection (ranking 9th in the traditional method is not accident prone in the modified method) and the same applies to Lougheed Hwy & Harris Rd. intersection.

- Finally, to prove that the locations identified by the modified method are more correctable by road improvements than the ones identified by the traditional method, the sums of correctable accident frequencies (Equation 3.13) for the top ranked 20 locations in each method were compared. In the case of the modified method the sum was 236.39 compared to 212.1 in the traditional method which indicates the potential advantage of the modified method in increasing the effectiveness of road safety improvement projects.

3.2.10 Application to the Concept of Forgiving Highways

Another potential application of the modified method is investigating the effects of the "forgiving highway" concept on accidents. This concept refers to a roadway which allows for some degree of driver error. Although human factors play the largest part in contributing to accidents, they are usually hard to identify and remedy. Engineering remedial measures, which are often easier to identify and remedy, can be applied to
counter human errors. For example, wider shoulders with adequate area to provide recovery space for run-off the road vehicles can eliminate some of the single-vehicle off-road accidents, even though these accidents involved some driver error.

As shown in Figure 3.3, highway agencies should devote their attention and spending on correcting accidents which belong to category 3, followed by accidents which belong to categories 5,6 and 7. Accidents in the last three categories are "somewhat correctable" by road improvements, perhaps using the concept of "forgiving highway". The degree of "forgiveness" can be assessed by the degree \( W_i \) with which accidents belong to the road environment group.

3. CONCLUSION

Traditional methods of identifying accident prone locations, or black spots do not account for accident contributing factors or causes. This leads to the identification of locations which may not be truly hazardous or accident prone from a road environment perspective. This Chapter described a new method, the modified black spot, for identifying APLs based on accident correctability by road improvements. The method utilizes safety experts' knowledge in classifying accidents into a finite set of categories. In practice, the categories can include any one or a combination of the three basic highway system components: the driver, the vehicle and the road. Realizing the complex interaction of these components within the accident environment, the procedure employs fuzzy pattern recognition algorithms to assign a degree of membership to each accident in each category. Accident correctability by road improvements is represented by accidents' membership in the road environment group.
The modified black spot program involves redefining accident frequency and rate to reflect accidents correctability and then using the Empirical Bayes technique to identify APLs. The program was applied to identify accident prone locations in the South Coast Region of the Province of British Columbia for several location categories and the results were compared with the traditional approach. The results indicated that the modified method has two main benefits over the traditional approach. First, only road related accidents are considered, resulting in a fewer number of accident prone locations. Secondly, The modified technique eliminates locations which are not correctable from a road authority perspective, thus increasing the potential effectiveness of road safety improvement programs.
CHAPTER 4

THE DETECTION PHASE: A COUNTERMEASURE-BASED PROGRAM

4.1 INTRODUCTION

In traditional black spot programs, for a location to be identified as accident prone, it must exhibit a higher accident occurrence than an established "norm". However, a problem that arises when analyzing accident prone locations, is that many of these locations do not have well-defined accident patterns for which countermeasures can be developed. And consequently, treating these locations may not be cost effective. To address this problem, this chapter describes another approach for the identification process. The approach, labeled "countermeasure based approach", is based on identifying locations that have over-representation of particular accident patterns. This facilitates the selection of countermeasures and identifies locations that are good candidates to be cost effectively treated.

4.2 THE COUNTERMEASURE-BASED PROGRAM

Traditional black spot programs start with a problem (high accident occurrence) and attempt to find solutions (countermeasures). The countermeasure-based approach reverses the traditional process of linking problems with solutions by first identifying main accident patterns that can be targeted by specific countermeasures and then searching for locations
which have over-representation of these patterns. The need for such an approach arises from the fact that many locations may have a relatively low frequency of accidents to be identified by the black spot programs, but may be effectively treatable by engineering countermeasures because of their well defined accident patterns.

To illustrate, consider, for example, a signalized intersection with a total of 35 accidents in three years. Similar signalized intersections with the same operating environment (reference group) have an average of 50 accidents in three years. This intersection will not be identified by traditional black spot programs as accident prone. However, if it is known that 25 out of the 35 accidents involved left turn collisions, then implementing a single countermeasure (e.g., addition of a left-turn lane, phasing, etc.) can be very cost effective.

In the countermeasure-based program, a location is identified as accident prone if it has over-representation of a particular accident type in the total number of accidents. Several accident patterns that can be targeted by specific countermeasures were identified. These types include:

- right angle
- left turn opposing
- straight ahead rear end
- left turn rear end
- right turn
- sideswipe
- head on
- run-off
- fixed object
- parked
- rail road
- pedestrian
- animal

There are several publications which describe common countermeasures for these accident patterns. An example of these efforts can be found in (Box, 1976; FHWA, 1981; and NAASRA, 1988).
The over-representation of particular accident types is assessed by the ratio of the number of a particular accident type to the total number of accidents at the location. To account for the random variation for this ratio, the approach utilizes the Empirical Bayes technique.

4.2.1 The Empirical Bayes Analysis

In sections 2.1.2.1 and 3.2.9.2, an Empirical Bayes approach was described to identify accident prone locations based on the observation of location accident rates. A slightly different approach will be used here. The observations are made of the ratio \( p \) of the number of a particular accident type \( x \) to the total number of accidents at the location \( n \). Before describing the methodology, the following notations are introduced:

- \( n_i \) = the total number of accidents at location \( i \) during specific period of time,
- \( x_i \) = the number of accidents of the particular type under investigation at location \( i \) from the \( n_i \) accidents,
- \( \bar{p}_i \) = the ratio of \( x_i \) to \( n_i \) (treated as a random variable),
- \( \bar{p} \) = the mean value for \( \bar{p}_i \) in the reference group,
- \( f_R(p) \) = probability density function associated with \( p \) across the reference group (prior distribution),
The Detection Phase: A Countermeasure-based Approach

\[ f(p|x_i, n_i) \]

= probability density function associated with \( p \) at location \( i \) given the observations \( x_i \) and \( n_i \) (posterior distribution).

In the derivation of the proposed method, it is assumed that at any given location, if the value of \( \tilde{p}_i \) is known (\( \tilde{p}_i = p \)), then the probability of occurrence of a certain value of \( x \) is given by the binomial distribution:

\[
P(x_i = x|n_i, \tilde{p}_i = p) = \binom{n_i}{x} p^x (1 - p)^{n_i-x} \quad (0 \leq x \leq n) \tag{4.1}
\]

The method proceeds as follows:

1. Establish appropriate reference groups which are homogeneous in both environment and operation. The following criteria were used to establish these groups:
   - location type (section/intersection),
   - environment (urban/rural),
   - highway class (2-lane, multi-lane, and freeway),
   - type of traffic control (signal, stop and yield, and uncontrolled).

2. For each location calculate the ratio (\( p \)) of each accident type (\( x \)) at the location to the total number of accidents (\( n \)). According to Maritz and Lwin (1989) and Calvin (1990), based on Equation 4.1, the prior distribution for \( p \), \( f_R(p) \), across the reference group is a beta distribution given by:

\[
f_R(p) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \Gamma(\beta)} p^{\alpha-1} (1 - p)^{\beta-1} \quad (0 < p < 1) \tag{4.2}
\]
The Detection Phase: A Countermeasure-based Approach

where $\alpha$ and $\beta$ are parameters of the prior distribution determined by fitting observations of all $x_i, n_i$ in the reference group to the Beta distribution. The mean and variance of the Beta distribution are:

$$\bar{p} = \frac{\alpha}{\alpha + \beta}$$  \hspace{1cm} (4.3)

$$s^2 = \frac{\alpha \beta}{(\alpha + \beta)^2 (\alpha + \beta + 1)}$$

$$= \frac{\bar{p}(1 - \bar{p})}{\alpha + \beta + 1}$$  \hspace{1cm} (4.4)

where $\alpha$ and $\beta$ have positive values.

3. The values of $\alpha$ and $\beta$ are obtained using the method of moments estimates (MME) by equating the mean and variance in equations 4.3 and 4.4 to the sample mean and variance which can be calculated as:

$$\bar{p} = \frac{1}{m} \sum_{i=1}^{m} \frac{x_i}{n_i}$$  \hspace{1cm} (4.5)

$$s^2 = \frac{1}{m-1} \sum_{i=1}^{m} \left( \frac{x_i}{n_i} - \bar{p} \right)^2$$  \hspace{1cm} (4.6)

4. The posterior distribution, $f(p|x_i, n_i)$, can then be obtained by updating the prior distribution with the location specific observations $x_i, n_i$ for the location under investigation. Calvin (1990) showed that the resulting distribution is also a beta distribution with parameters:

$$\alpha_i = \alpha + x_i$$  \hspace{1cm} (4.7)
\[ \beta_i = \beta + n_i - x_i \]  

(4.8)

Which implies that

\[ f(p|x_i, n_i) = \frac{\Gamma(\alpha_i + \beta_i)}{\Gamma(\alpha_i) \Gamma(\beta_i)} p^{\alpha_i-1} (1-p)^{\beta_i-1} \]  

(4.9)

5. A location then is considered as having an over-representation of a particular accident type if the probability is significant that its observed \( p \) exceeds the reference group value \( P_{\text{ref}} \). That is true, if:

\[
\left[ 1 - \int_0^{P_{\text{ref}}} \frac{\Gamma(\alpha_i + \beta_i)}{\Gamma(\alpha_i) \Gamma(\beta_i)} p^{\alpha_i-1} (1-p)^{\beta_i-1} \, dp \right] > \delta
\]

(4.10)

where \( \delta \) is taken to be any value such as 0.95 or 0.99, and \( P_{\text{ref}} \) is calculated as:

\[ P_{\text{ref}} = \frac{\sum_{i=1}^{m} x_i}{\sum_{i=1}^{m} n_i} \]

(4.11)

4.4.2 Applications

To investigate the effectiveness of the countermeasure-based program in eliminating potential accidents, it was applied to the set of all signalized intersections in the South Coast Region of the province of British Columbia using accident data from 1989 to 1991. As an illustration, two accident types were considered: right angle accidents, and left turn opposing accidents. Identified accident prone locations of the two accident types are shown in Figures 4.1 and 4.2. The critical ratio in the figures was calculated by solving
equation 4.10 for the value of $p$ given the value of $\delta$. The resulting value will correspond to the critical ratio $p_{cr}$. If the observed value for $p$ is greater than $p_{cr}$, given the observed total number of accidents, the location is considered accident prone for the particular accident type. A value of 0.99 was used for $\delta$.

One major advantage of using the Empirical Bayes approach is to correct for the bias that occurs at locations with a low total number of accidents. Since the variance of estimated $\hat{p}$ is inversely proportional to the total number of accidents $n$, then the regression to the mean bias will be higher for locations with small value of $n$. To illustrate, consider a location which has only two accidents and one of them is right angle, then the $x/n$ ratio for right angle accidents will be 50% which is considered high. This high ratio has a high probability to be due to chance alone and subsequently it does not mean that the location should be considered accident prone. The Empirical Bayes method accounts for this bias by shrinking locations with a low number of accidents more towards the distribution mean and thus they will have a lower probability of being identified as accident prone. This effect is shown in Figures 4.1-4.2 where many locations with low accidents and high $x/n$ were not identified as accident prone.
Figure 4.1 Right Angle Accident Prone Locations for Signalized intersections in the South Coast Region
Figure 4.2 Left-turn Opposing Accident Prone Locations for Signalized Intersections in the South Coast Region
4.2.3 Discussion

As noted previously, the main issue in any highway safety improvement program is the demonstration of the cost effectiveness of the whole program. The identification of accident prone locations should consider locations that are both "truly" hazardous (as in the case of the modified black spot program) and which can be cost effectively treated. The latter criterion is the backbone of this program. The analysis of accident prone locations is usually undertaken by defining different accident patterns and matching these patterns with different countermeasures. Several publications exist which outline different accident patterns and the countermeasures effective in reducing these accidents. The application of the countermeasure-based program not only facilitates the selection of countermeasures but improve chances of getting better return for the money spent in highway safety improvement programs.

The main difference between the countermeasure-based approach and traditional black spot programs lies in the identification of accident prone locations. In traditional black spot programs, where accident patterns are not considered, locations with a higher number of accidents are more likely to be identified as accident prone. However, in the countermeasure-based approach, locations are identified as accident prone when they exhibit well-defined accident patterns. To illustrate, Tables 4.1 and 4.2 show intersections that exhibited over-representation of right angle and left-turn opposing accidents along with their ratios \( p_i / p_{cr} \). For comparison, The Empirical Bayes approach described by Higle an Witkowski (1988) was used to identify critical accident rates for these intersections. The ratio of the observed accident rate to the critical rate is shown in Table 4.1 (an intersection is considered accident prone if this ratio exceeds one).
Table 4.1 A Comparison between the Traditional Black Spot and the Countermeasure-Based Programs (Right Angle Accidents)

<table>
<thead>
<tr>
<th>Intersection Name</th>
<th>Countermeasure-Based Program (Right Angle Pattern)</th>
<th>Black Spot Program</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Right-angle ratio (critical ratio)</td>
<td>Accident rate (critical ratio)</td>
</tr>
<tr>
<td>------------------------------</td>
<td>-----------------------------------------------------</td>
<td>--------------------------</td>
</tr>
<tr>
<td>Hwy 99A &amp; 88th Ave.</td>
<td>1.71 Yes</td>
<td>2.8 Yes</td>
</tr>
<tr>
<td>Hwy 15 &amp; 16th Ave.</td>
<td>1.70 Yes</td>
<td>1.17 Yes</td>
</tr>
<tr>
<td>Hwy 1A &amp; Boundary Rd.</td>
<td>1.69 Yes</td>
<td>0.4 No</td>
</tr>
<tr>
<td>Hwy 15 &amp; 64th Ave.</td>
<td>1.66 Yes</td>
<td>1.22 Yes</td>
</tr>
<tr>
<td>Hwy 99A &amp; 64th Ave.</td>
<td>1.58 Yes</td>
<td>1.72 Yes</td>
</tr>
<tr>
<td>Hwy 1A &amp; 208th St.</td>
<td>1.49 Yes</td>
<td>0.82 No</td>
</tr>
<tr>
<td>Hwy 1A &amp; Hwy 10</td>
<td>1.4 Yes</td>
<td>1.33 Yes</td>
</tr>
<tr>
<td>Hwy 1A &amp; Royal Oak Ave.</td>
<td>1.38 Yes</td>
<td>0.7 No</td>
</tr>
<tr>
<td>Langley By-Pass Crosses</td>
<td>1.35 Yes</td>
<td>2.36 Yes</td>
</tr>
<tr>
<td>Hwy 1A &amp; Pipe Rd.</td>
<td>1.19 Yes</td>
<td>0.86 No</td>
</tr>
<tr>
<td>Hwy 99A &amp; 72nd Ave.</td>
<td>1.14 Yes</td>
<td>1.66 Yes</td>
</tr>
<tr>
<td>Hwy 1A &amp; 184th St.</td>
<td>1.09 Yes</td>
<td>0.5 No</td>
</tr>
<tr>
<td>Hwy 7 &amp; Blue Mountain St.</td>
<td>1.08 Yes</td>
<td>0.71 No</td>
</tr>
<tr>
<td>Hwy 1A &amp; 216th St.</td>
<td>1.04 Yes</td>
<td>0.7 No</td>
</tr>
<tr>
<td>Hwy 1A &amp; 14th Ave.</td>
<td>1.04 Yes</td>
<td>0.54 No</td>
</tr>
<tr>
<td>Hwy 99A &amp; 80th Ave.</td>
<td>1.01 Yes</td>
<td>1.6 Yes</td>
</tr>
</tbody>
</table>
Table 4.2 A Comparison between the Traditional Black Spot and the Countermeasure-based programs (Left-turn Opposing Accidents)

<table>
<thead>
<tr>
<th>Intersection Name</th>
<th>Countermeasure-Based Program</th>
<th>Black Spot Program</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(Left-Turn Opposing pattern)</td>
<td>Accident prone</td>
</tr>
<tr>
<td></td>
<td>Left-turn ratio</td>
<td>Accident rate</td>
</tr>
<tr>
<td></td>
<td>critical ratio</td>
<td>Critical rate</td>
</tr>
<tr>
<td></td>
<td>Opposing accident prone</td>
<td>Accident prone location</td>
</tr>
<tr>
<td>Canada Way, Edmonds</td>
<td>1.81</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>King Edward Ave. Crosses</td>
<td>1.57</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>1.84</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Hwy 1A &amp; 64th Ave.</td>
<td>1.36</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>2.36</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Hwy 99A &amp; 64th Ave.</td>
<td>1.21</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>1.72</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Hwy 15 &amp; JCT Hwy 1A</td>
<td>1.17</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Hwy 99A &amp; 152nd Ave.</td>
<td>1.15</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>0.93</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Hwy 1A &amp; County Line Rd.</td>
<td>1.02</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td></td>
</tr>
</tbody>
</table>
As shown in Table 4.1, eight out of the 16 intersections that exhibited over-representation of right angle accidents were not identified as accident prone by the traditional black spot program. Hwy 1A & Boundary Rd. intersection, which has a right angle ratio 1.69 times higher than the critical ratio, has an observed accident rate much lower than the critical rate. Out of the 20 accidents which occurred at this intersection, 12 involved right angle collisions. This indicates that if a common cause for these 12 accidents can be found, then implementing a single countermeasure will be very cost effective. The same applies to the other seven intersections which were not identified by the black spot program.

Table 4.2 shows approximately the same trend. Only three out of the seven intersections which exhibited over-representation of left turn opposing accidents were identified as accident prone by the traditional black spot program. The top ranked intersection (Canada way & Edmonds), which has a left turn opposing ratio 1.81 times higher than the critical ratio, has an observed accident rate much lower than the critical rate. Seventeen out of the 29 accidents which occurred at this intersection involved a left turn opposing collision. This indicates that providing a countermeasure such as (left turn lane, phase, etc.) can be very cost effective.

4.3 CONCLUSION

This chapter described the second component of the detection phase, the countermeasure-based program. The program reverses the traditional process of linking problems with solutions by first identifying main accident patterns that can be targeted by specific countermeasures and then searching for locations which have over-representation of these patterns. The over-representation of particular accident type is assessed by the ratio of the
number of a particular accident type to the total number of accidents at the location. The Empirical Bayes approach described in Chapters 2 and 3 was slightly modified and applied in this program to account for the random variation in accident types ratio. The program was applied to identify two different accident type prone locations in the South Coast Region of B.C. The results indicated that many locations identified in the countermeasure-based program because of their well-defined accident patterns were not accident prone according to the traditional approach. The application of this program should facilitate the selection of countermeasures and improve chances of getting better return for the money spent in highway safety improvement programs.
5.1 INTRODUCTION

The diagnosis phase is concerned with the analysis of the nature and contributing factors of safety problems at the locations identified in the detection phase (both programs) and the development of location engineering improvements. The basic element of the analysis during the diagnosis phase is to find accidents' contributing factors among the operational, physical, and environmental features at each location. This is probably the most complex task of traffic safety (Mchane and Roess, 1990). The analysis lends itself to the knowledge-based approach since it involves a great deal of judgment and experience by the safety engineer. Knowledge-based expert systems provide a means to incorporate experts' knowledge, experience, judgments and other historical information into one system which can be used to aid and guide practitioners. This chapter describes a prototype knowledge-based system that performs accident prone locations analysis.

5.2 ANALYSIS OF ACCIDENT PRONE LOCATIONS

Once a location has been identified as accident prone, a search for effective safety countermeasures begins. The process of identifying effective countermeasures includes the following steps. First, accident data (usually for the last 2-3 years) are analyzed to identify over-represented clusters of particular accident types. This is done by comparing the actual percentage of accident types at the location with the average percentage of these types at similar locations. Secondly, location-specific data (physical and
operational) are identified. The analyst then utilizes this information to identify possible causes of the over-represented accident types. Two questions need to be answered: 1) what existing conditions at the location could contribute to the occurrence of accidents?, and 2) what changes, if any, can be made to reduce the number and/or severity of these accidents?. The over-representation of a certain accident type may point to a specific problem. For example, an over-representation of wet weather accidents may be attributed to a poor pavement texture or a poor drainage system or both. Once accident causes have been identified, the third step is to generate a list of possible countermeasures and then finally, the range of possibilities is narrowed to a small number of the likely effective countermeasures. The final choice will generally be based on judgment and experience utilizing countermeasures which have been successful in similar circumstances.

5.3 THE NEED FOR USING THE KNOWLEDGE-BASED APPROACH

Unfortunately, the problem of accident prone locations analysis is not as simple as it may appear from the previous section. Establishing accident causes may vary greatly with the situation and the location investigated. Each situation and location has its unique features which may require the analyst to apply his knowledge in an innovative way. Furthermore, the issue of matching accident patterns and countermeasures is usually uncertain and requires all of the analyst's knowledge of road design, operations, controls and safety. The selection of countermeasures is usually made based on engineering experience and judgment which often contain uncertainty and inconsistency. Another dimension to the problem is the nature of accident data which in many cases are uncertain, unreliable and may even be conflicting.
All the attributes of the accident prone locations analysis suggest that an expert system approach may be effective in dealing with the problem. Three main criteria of the expert system approach motivate its adoption to the location analysis problem:

1. **Symbolic information.**

   The ability to deal with knowledge in non-numerical (symbolic) form is one of the most important advantages of expert systems in contrast to conventional techniques. This ability, according to Wild and Berns (1990), facilitates first, the thinking about problems in terms of involved concepts and relationship between them, and secondly, it makes it easier to incorporate knowledge which is only present as human expertise and heuristics.

2. **Lack of explicit algorithms.**

   If a problem can be adequately solved by an algorithm solution then it should not be a candidate for an expert system approach. The expert system approach is more suited for problems that are ill-structured and/or lack explicit algorithms as they depend on the experience and judgment of the analyst.

3. **Uncertain and Fuzzy Information**

   Dealing with real world data always involve processing uncertain, missing and inaccurate data. Many techniques to handle such difficulties have been developed in the expert system domain.
5.4 INTRODUCTION TO KNOWLEDGE-BASED EXPERT SYSTEMS

Expert systems are a sub-field of the Artificial Intelligence (AI) technology (Figure 5.1). Artificial Intelligence is the branch of computer science that studies how computers can be used to simulate or duplicate functions of the human brain. Knowledge-based expert systems are computer programs that include a simulation of the reasoning and problem-solving process of human experts. These programs offer a means to capture the knowledge and experience of current professionals and organize, save and apply this information to be used as assistants, decision aids, or training aids by the less-experienced professionals. The basic differences between knowledge-based expert systems and conventional programs outlined by Wentworth (1990) are provided in Table 5.1.

5.4.1 Basic Structure of an Expert System

In a typical expert system, the domain knowledge needed for understanding, formulating and solving the problem is stored in a knowledge base as shown in Figure 5.2. It contains permanent facts and rules or other knowledge types that an expert uses to derive his or her conclusions. The actual processing of the knowledge base is performed by an inference engine which receives the information from the environment (user or other information systems) and uses the contents of the knowledge base to reach conclusions while aiming at solving the given problem (Linnainmaa, 1990). Problem specific data and the conclusions are stored in a short-term memory. Long-term memory might include records or case-histories of previous consultations for quick-reference to the current problem. The user interface allows a user to provide problem specific data to the inference engine and to receive the results. The explanation facility enables the expert system to justify its questions and conclusions upon request.
Figure 5.1 Major Subfields of Artificial Intelligence
(Source Linnainmaa, 1990)
Table 5.1 Conventional Programs Versus Knowledge-Based Expert Systems
(Source, Wentworth 1990).

<table>
<thead>
<tr>
<th>Conventional Program</th>
<th>Knowledge-based Expert System</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stated equations which can be proven. If correct numerical data is provided, a correct answer will result</td>
<td>Usually based on rules of thumb (or other knowledge representation) that are generally reliable, but not always correct. These are concepts and cannot be reduced to formulae or numbers</td>
</tr>
<tr>
<td>Provides answers only</td>
<td>Can explain its logic and reasoning</td>
</tr>
<tr>
<td>Needs all data called for to operate</td>
<td>Can function with incomplete data</td>
</tr>
<tr>
<td>Often programmed in isolation from domain experts and users.</td>
<td>Development team includes domain expert and users.</td>
</tr>
<tr>
<td>May be extremely difficult to examine imbedded knowledge.</td>
<td>Provides capability to easily examine knowledge base.</td>
</tr>
</tbody>
</table>
It has to be noted that the separation between the inference engine and the knowledge base is one of the most important features of an expert system. Its goal is to always keep the inference engine untouched and change only the contents of the knowledge base if more expertise is to be added (Linnainmaa, 1990).

5.4.2 Expert Systems Developing Tools

Currently, most simple knowledge-based systems are created using expert system shells, because they are relatively easy to use when compared with actual programming languages. Shells of various sophistication levels are available for all kinds of computers. Their properties can vary significantly, for example, they may have forward or backward or forward and backward chaining possibilities. They may also include some kind of uncertainty management. Most expert systems that are currently in operational use have been developed with shells.

In more sophisticated expert systems, special AI languages such as LISP and PROLOG are frequently used. They differ from conventional programming languages by providing effective possibilities to handle symbolic information and data structures that change very dynamically in run time. Conventional programming languages such as C and Pascal can also be used to develop expert systems. However, this requires very skillful programmers and a great deal of effort. It should also be noted that the remarkable advances in the area of developing expert system shells has produced very capable and sophisticated shells which reduce the need to use AI or conventional programming languages.
The Diagnosis Phase

Figure 5.2 Basic Structure of an Expert System
5.4.3 Representing and Handling Uncertain Knowledge

As noted previously, a significant portion of the knowledge contained in knowledge-based systems is usually based on experts' judgment and experience which often contain uncertainty and inconsistency. There are also uncertainties accompanying problem's data. Therefore, any knowledge-based system should be capable of providing mechanisms for handling this uncertainty. Several methods have been proposed for representing and reasoning under uncertainty in knowledge-based systems, ranging from simple methods such as certainty factors to the more computationally intensive such as fuzzy logic.

The most simple and widely used technique for representing uncertain knowledge is using *certainty factors* (confidence factors). A certainty factor is a numeric coefficient that describes the strength of belief (level of confidence) assigned to a fact or a conclusion. They are usually assigned by default or by user input. They typically range between some lower bound (usually 0) to an upper bound (usually 1 or 100). Several methods have been developed to combine the effects of these factors when rules are used to produce conclusions (Winston, 1984; and Shortliffe and Buchanon, 1985). However, the use of certainty factors is criticized by several researchers (Henkind and Harrison, 1988) for not being able to properly handle mutual dependencies of the uncertainties.

Other methods to handle uncertainty include Bayesian methods and fuzzy logic. Bayesian inference is based on the use of conditional probability; that is, the probability of one event occurring given prior knowledge of the probability of one or more other events occurring. Fuzzy logic extends fuzzy set theory to permit inexact or approximate inference with fuzzy concepts. Most expert system shells (including Comdale\X) support the use of certainty factors and very few support fuzzy or Bayesian methods largely because their computational intensity.
5.5 THE ACCIDENT PRONE LOCATIONS ANALYSIS KNOWLEDGE-BASED SYSTEM

The idea of using the expert system approach to perform accident prone locations analysis is not new. Several researchers, such as Spring et al. (1987), recognized the need for such a system and demonstrated its feasibility. They concluded that "An expert system to performing the location analysis portion of highway safety improvement programs appears feasible......whether it can be reasonably designed and implemented is a question that must still be answered." Several efforts were undertaken to build expert systems directed at solving particular safety problems. Examples for such systems may be found in Spring (1988) and Seneviratne (1990) for intersections safety; Zhou et al. (1991) for roadside barrier installation; and Ramache (1990) for fixed roadside object problems.

Several common observations can be made about these efforts:

- First, their goal was to produce systems that are supposed to perform a complete location analysis with little or no intervention from the safety engineer. This is a very difficult task given the size and complexity of the safety problem. To make the problem manageable, these systems only targeted particular safety problems (specific accident patterns, specific location types, specific countermeasures, etc.) and concluded that a system that covers all safety aspects may require huge resources and efforts.

The system described here, is not intended to eliminate or replace the safety analyst but rather as an aid to alert him to possible contributing factors and effective countermeasures. And thus, the system can cover more aspects of safety analysis.
• Secondly, no attempt was made to link the diagnosis process to the accident database directly.

Implementing this link in this system serves two goals: 1) a first pass can be made automatically and without any human intervention through accident records at an accident prone location to produce summary information (accident chain events; apparent contributing factors, etc.). This would relieve the analyst from performing these routine tasks, and 2) assess the uncertainty of the information provided in the accident database by performing logic checks and weighing the credibility of conflicting information. This task may be extremely difficult for an analyst; a typical accident prone location may have more than a hundred accidents to analyze, each with more than 70 items of information.

• Thirdly, all these systems targeted the analysis (diagnosis) process separately from the detection process. No effort was made to link the two processes together. Many information produced from the detection phase can facilitate the diagnosis process.

The diagnosis process in this system is directly tied to the detection process. It makes use of the information available from the detection process to facilitate the diagnosis. The information includes: over-represented (predominant) accident patterns; the degree of over-representation; the split of location's accidents by severity for each predominant pattern, etc.

5.5.1 Prototype Development

Development of this prototype includes five main steps: 1) selection of the development tool; 2) knowledge acquisition; 3) problem solving strategy; and 4) the prototype
development (programming) and 5) prototype verification and validation. Figure 5.3 shows general components of the knowledge-based system and their relationships. Arrows on the Figure show flow of information and/or control.

5.5.1.1 The Development Tool

The tool used to develop the knowledge base is the Comdale/X expert system shell (Comdale Technologies, 1993). There are several reasons for the choice of the Comdale/X shell. First, it has many built-in features and advantages that make development of an expert system simple and straight-forward. These advantages include:

- A totally customized windowed user interface and a hypertext facility including graphical presentations.
- Simultaneous backward and forward chaining capabilities.
- Debugging features (watch variables and rule tracing).
- Excellent meta-knowledge capabilities, which include customized questions and explanations, hypertext documents, forms, and graphics.

Second, Comdale/X was available at the B.C. Ministry of Transportation and Highways. Third, the knowledge-based system developed in this research does not require very sophisticated shells and any shell which posses the main features described above will do.
The Diagnosis Phase

Figure 5.3 Components of Accident Prone Locations Analysis Knowledge-based System
Knowledge base units in Comdale/X (Figure 5.4) can be grouped into three categories: structural, procedural, and meta-knowledge. Structural knowledge consists of rules (conditions and conclusions) and facts (classes and objects). Procedural knowledge units are used to direct the inference engine to perform specific tasks (search strategies, etc.). Meta-knowledge provides explanations and justifications to the user (Meech, 1990).

**Objects** are physical or conceptual entities. All objects have at least one attribute. An attribute describes the property of an object. A description of the entity is completed with a value which explains the particular or the special nature of the object. The combination of object, attribute and value is termed a "keyword triplet". which is written in the form:

\[
\text{Object.Attribute.Value (e.g. Intersection.Traffic\_Control.Stop\_Sign)}
\]

Associated with each keyword triplet is a number of facets which are used to specify a wide variety of actions or functions related to the keyword triplet such as questions to be asked, explanations, default values, restrictions on values, source of information, etc.

**Classes** represent the relationships which exist among different objects. For example, all accident patterns (Right-Angle, Wet, etc.) are a member of one class; Accident-Pattern. By defining a class, all common attributes of particular objects can be defined. If an object is defined to be a member of the class it will *inherit* all the attributes of that class. Classes can also be members of other classes (Superclasses). Each class has *public attributes* which are inheritable by all subclasses and member objects and *private attributes* which are inherited only by objects of the class but not subclasses.
Figure 5.4 Knowledge Base Units in Comdale/X
Rules represent reasoning knowledge and handle complex interaction between facts (Comdale Technologies, 1993). They are created to associate various actions which should be taken when specific conditions are met. Rules are written in an IF-AND-OR-THEN-ELSE format. The IF-AND-OR part of the rule is called the premise(condition), while the THEN-ELSE part is called the conclusion. Rules can be grouped and assigned to Rulesets. These rulesets can then be executed as one group. The rules are usually not definitive or, in other words, there are uncertainties associated with them. Basically, two types of uncertainty are considered: uncertainty in the premise, and uncertainty in the conclusion. Each keyword triplet in the premise is associated with a factor indicating its degree of certainty (i.e. how sure the system or the user that the evidence exist). Conclusion statements are accompanied by a certainty factor which reflects the confidence in this conclusion statement. Rules also have attributes which describe their characteristics, explanations, how uncertainty should be handled, priority, etc. A more detailed description of Comdale/X knowledge base units can be found in (Comdale Technologies, 1993).

5.5.1.2 Knowledge Acquisition

Knowledge acquisition is the process in which information that experts use to solve a particular problem is extracted and organized. The knowledge acquisition process is probably the most crucial and difficult part in the development of expert systems (Waterman, 1986). It requires a high degree of skill by the knowledge engineer. Two sources are utilized for knowledge acquisition in the domain of accident prone locations analysis: technical literature and interviews with domain experts (Highway Safety Branch staff). Technical literature include sources such as engineering text books, journals,
conference proceedings, etc. These sources are generally well organized and ready to use. There are several publications which attempted to document the general "rules of thumb" used in analyzing accident data at specific locations. An example of these efforts can be found in (FHWA, 1981; NAASRA, 1988; Box, 1976; and Missouri Highway and Transportation Department, 1990). These publications were extensively used to extract initial knowledge about the problem. The knowledge extracted from these publications is very important but usually insufficient for analyzing location-specific cases. This is why the second source, interviews with domain experts, is crucial. It comprises knowledge from long term experience and skill in solving various accident prone locations analysis problems.

5.5.1.3 Problem Solving Strategy

Problem solving strategies in expert systems usually follow one of two approaches (Maher, 1987; Adams et al. 1987): the derivation approach and the formation approach. In the derivation approach, the most appropriate solution is selected from a finite set of predefined solutions. The approach requires that all possible solutions to a problem be listed and justified for the context of the particular problem at hand. The formation approach, on the other hand, is preferable to solve problems in which all possible solutions can not be predefined due to practical reasons. The approach is implemented by forming a complete solution from components of solutions stored in the knowledge base. The derivation approach may be useful in solving diagnosis, interpretation and classification problems, while the formation approach is generally suitable for planning and design problems.
As a diagnosis problem, the solving strategy used for the accident prone locations analysis is based on derivation. Generally, in diagnosis problems, a system's symptoms are examined to find a cause (and a remedy). Diagnosing an accident prone location involves the evaluation of location's symptoms (over-representation of specific accident patterns, high accident severity, etc.) to determine a specific cause or a set of candidate causes, and to develop from these causes the best remedy (countermeasure) or a set of remedies. Table 5.2 shows the relation between different predominant accident patterns, causes, and possible countermeasures as used in the system.
Table 5.2 Relation Between Predominant Accident Patterns, Causes, and Countermeasures, (Sources: FHWA, 1981; NAASRA, 1988; Box, 1976; and Missouri Highway and Transportation Department, 1990)

<table>
<thead>
<tr>
<th>Predominant Accident Patterns</th>
<th>Causes</th>
<th>Countermeasures</th>
</tr>
</thead>
</table>
| Rear-end Collisions           | Lack of adequate gaps (unsignalized intersections) | • Provide traffic signal if warranted (Check MUTCD)  
• Provide Stop sign if warranted (Check MUTCD) |
| Excessive speed on approaches |        | • Enforce speed limit  
• Reduce speed limit on approaches |
| Crossing pedestrians          |        | • Provide pedestrian walk phase  
• Improve signing for pedestrian crosswalks |
| Large number of right turning vehicles |        | • Increase curb radii  
• prohibit right turns  
• provide separate right-turn lane |
| large number of left turning vehicles |        | • prohibit left turns  
• Provide separate left turn lane  
• Provide exclusive left turn phase |
| Inadequate signal timing      |        | • Increase amber phase  
• Provide all-red phase  
• Coordinate with other signals |
| Poor visibility of signals    |        | • Install 12" signal lenses  
• Add additional signal heads  
• Relocate signals  
• Provide backboard with reflecting border  
• Remove obstacles that block signal view  
• Install/Improve advance warning devices |
| Inadequate warning signs      |        | • Install intersection warning signs  
• Relocate intersection warning signs |
| Signals not warranted         |        | • Remove signals (check MUTCD) |

The Diagnosis Phase
### Table 5.2 Relation between predominant accident patterns, causes, and countermeasures (Cont.)

<table>
<thead>
<tr>
<th>Predominant Accident Patterns</th>
<th>Causes</th>
<th>Countermeasures</th>
</tr>
</thead>
</table>
| Right-Angle Collisions        | Restricted sight distance (unsignalized intersections) | • Remove sight obstructions  
• Prohibit parking  
• Reconstruct intersection to improve grades  
• Realign Intersection  
• Install signals (check MUTCD)  
• Install Stop sign (check MUTCD) |
| Excessive speed on approaches |                                            | • Enforce speed limit  
• Reduce speed limit on approaches                                              |
| Lack of adequate gaps         |                                            | • Provide traffic signal if warranted (Check MUTCD)                              |
| (unsignalized intersections)  |                                            |                                                                                |
| Inadequate signal timing      |                                            | • Increase amber phase  
• Provide all-red phase  
• Coordinate with other signals                                                  |
| (Signalized intersections)    |                                            |                                                                                |
| Inadequate warning signs      |                                            | • Install intersection warning signs  
• Relocate intersection warning signs                                             |
| Poor visibility of signals    |                                            | • Install 12" signal lenses  
• Add additional signal heads  
• Relocate signals  
• Provide backboard with reflective border  
• Remove obstacles that block signal view  
• Install/Improve advance warning devices |
| (Signalized intersections)    |                                            |                                                                                |
| Left-turn opposing collisions | Large volume of left-turning vehicles       | • Install Signal (check MUTCD)  
• Install Stop sign (check MUTCD)  
• Provide exclusive left-turn phase  
• Provide separate left-turn lane  
• Prohibit left-turns                                                             |
Table 5.2 Relation between predominant accident patterns, causes, and countermeasures (Cont.)

<table>
<thead>
<tr>
<th>Predominant Accident Patterns</th>
<th>Causes</th>
<th>Countermeasures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left-turn opposing collisions</td>
<td>Restricted sight distance</td>
<td>• Provide separate left-turn lanes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Remove obstacles</td>
</tr>
<tr>
<td></td>
<td>Inadequate signal timing</td>
<td>• Increase amber phase</td>
</tr>
<tr>
<td></td>
<td>(Signalized Intersections)</td>
<td>• Provide all-red phase</td>
</tr>
<tr>
<td>Pedestrian-vehicle collisions</td>
<td>Restricted sight distance</td>
<td>• Remove sight obstructions</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Prohibit curb parking</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Install pedestrian crossing</td>
</tr>
<tr>
<td></td>
<td>Inadequate signal timing</td>
<td>• Change timing of pedestrian phase</td>
</tr>
<tr>
<td></td>
<td>(Signalized intersections)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Inadequate Signals</td>
<td>• Install pedestrian signals (Check MUTCD)</td>
</tr>
<tr>
<td></td>
<td>Inadequate gaps</td>
<td>• Install traffic signal (Check MUTCD)</td>
</tr>
<tr>
<td></td>
<td>(Unsignalized intersections)</td>
<td>• Install pedestrian crosswalks and signs</td>
</tr>
<tr>
<td>Night-accidents</td>
<td>Poor highway lighting</td>
<td>• Install/Improve highway lighting</td>
</tr>
<tr>
<td>Wet/icy pavement accidents</td>
<td>Slippery surface</td>
<td>• Overlay pavement</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Provide SLIPPERY WHEN WET sign</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Groove existing pavement</td>
</tr>
<tr>
<td></td>
<td>Poor drainage</td>
<td>• Improve drainage</td>
</tr>
<tr>
<td>Sideswipe collisions</td>
<td>Inadequate acceleration/deceleration</td>
<td>• Provide accel/decel lanes</td>
</tr>
<tr>
<td></td>
<td>lanes</td>
<td>• Lengthen existing accel/decel lanes</td>
</tr>
<tr>
<td></td>
<td>Inadequate pavement markings</td>
<td>• Improve/Install central and lane lines</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Install reflectionized lines and edges</td>
</tr>
<tr>
<td></td>
<td>Inadequate lane width</td>
<td>• Widen lanes</td>
</tr>
<tr>
<td></td>
<td>Inadequate lane change signs</td>
<td>• Install lane change warning signs</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Install overhead lane use signs</td>
</tr>
<tr>
<td></td>
<td>Inadequate shoulders</td>
<td>• Improve shoulders</td>
</tr>
</tbody>
</table>
Table 5.2 Relation between predominant accident patterns, causes, and countermeasures

(Cont.)

<table>
<thead>
<tr>
<th>Predominant Accident Patterns</th>
<th>Causes</th>
<th>Countermeasures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Head-on collisions</td>
<td>Inadequate pavement markings</td>
<td>• Improve/Install central and lane lines</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Install reflectionized lines and edges</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Provide median barrier to separate opposing flow</td>
</tr>
<tr>
<td>Restricted sight distance</td>
<td></td>
<td>• Install no passing zones</td>
</tr>
<tr>
<td>Collision with parking vehicles</td>
<td>Improper parking</td>
<td>• Prohibit parking</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Enforcement</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Post parking restrictions near driveways</td>
</tr>
<tr>
<td>Angle parking</td>
<td></td>
<td>• Convert to parallel parking</td>
</tr>
</tbody>
</table>
5.5.1.4 Prototype Features

As noted previously, the main structural knowledge base units in Comdale/X are: classes, objects, and rules. All predominant accident patterns are represented as classes and are also a member of the superclass "Accident-Pattern". This allows them to inherit the public attributes of the superclass. Rules represent the uncertain logical relationships between accident patterns, causes, and countermeasures. The relation between each cause and predominant accident patterns are represented by a set of rules (ruleset) which is fired when the system attempts to instantiate a certain cause. The same cause may be instantiated from different predominant accident patterns. For example, the cause "Inadequate Signal Timing" can be instantiated due to three predominant accident patterns: left-turn opposing, right-angle, and rear-end accidents. In each case a different set of rules are fired to instantiate the cause.

Any information used by rules for reasoning is treated as objects. For example, to instantiate the cause "Poor Signals Visibility", four objects need to be known: number of signal heads provided, signal lens sizes, approximate distance from intersection at which signals become visible and the effect of background lighting. Each of these objects can have different levels (values). For example, the approximate distance from intersection at which signals become visible can have one of the following values: less than 50m, between 50m and 100m, between 100m and 200m, between 200m and 300m, and greater than 300m. Since the object can be assigned only one of these values, they are represented by an exclusive set. As soon as one of these values are selected (become TRUE) the rest are assigned a "FALSE" value. Table 5.3 shows examples for the objects needed to instantiate some of the causes. A cause will be considered true (valid hypothetically) if its degree of belief exceeds a certain threshold level. The value for this threshold level was selected to be 50%. However, the analyst can change this value. Details on the calculation...
of the degree of belief in causes will be presented in the next chapter. The relation between different accident causes and possible countermeasures is represented by rulesets.

When the system is started it will first ask the analyst to supply the location identification information (segment and kilometer). The system opens the accident prone locations database and downloads information regarding accidents that have occurred at the location during the last three years. The system then invokes a C++ module which produces a statistical summary for the information in the accident records and the output of the detection phase. These statistical information include:

- The method by which the location was identified as accident prone (Modified Black Spot or Countermeasure-Based) and the degree of proneness (the ratio between the observed measure to its critical value),

- Predominant accident patterns and the degree of over-representation. The C++ module uses the Empirical Bayes technique (similar to the approach described in Chapter 4). An accident pattern is considered predominant if its ratio is 75% or greater of the critical ratio,

- The split of location's accidents by severity (property damage only, injury, fatal) for each predominant pattern, and

- Other miscellaneous information such as location type, speed limit, traffic control device, accident chain events, etc.

Based on the predominant accident patterns, the system identifies which causes need to be instantiated and which rulesets to be fired. In doing so, the system attempts to use the
information available in accident records. However, accident records do not provide all necessary information and the analyst may be asked to provide answers to questions regarding the missing information. The system uses the built-in screen management facilities of Comdale/X to provide the analyst with these questions. An example of Comdale/X screens are shown in Figure 5.5. The analyst can ask the system to "explain" a question or justify "why" the question is being asked.
Table 5.3 Examples of the Objects Needed to Instantiate Some of the Causes

<table>
<thead>
<tr>
<th>Accident Cause</th>
<th>Objects</th>
<th>Levels (Values)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Restricted Sight Distance at Signalized Intersections</td>
<td>Value of Parking Distance from Intersection</td>
<td>Greater than 50m, Between 30m and 50m, Between 20m and 30m, Between 15m and 20m, Less than 15m</td>
</tr>
<tr>
<td>Degree of Physical Obstructions</td>
<td></td>
<td>Not a problem, Not much, Neutral, Somewhat, Significant</td>
</tr>
<tr>
<td>Effect of Approaching grades</td>
<td></td>
<td>Not a problem, Not much, Neutral, Somewhat, Significant</td>
</tr>
<tr>
<td>Intersection Angle Value</td>
<td></td>
<td>90 degrees, 75-90 degrees, 60-75 degrees, 45-60 degrees, Less than 45 degrees</td>
</tr>
<tr>
<td>Inadequate Signal Timing at Signalized Intersections</td>
<td>Value of the amber phase</td>
<td>Greater than 4 seconds, Four seconds, Three and half seconds, Three seconds, Less than three seconds</td>
</tr>
<tr>
<td>All-red phase</td>
<td></td>
<td>Provided, ****, Provided but not sufficient, ****, Not provided</td>
</tr>
<tr>
<td>Efficiency of signal phasing</td>
<td></td>
<td>Very effective, Effective, Fair, Poor, Very poor</td>
</tr>
</tbody>
</table>
The Diagnosis Phase

Table 5.3 Examples of the objects needed to instantiate some of the causes

<table>
<thead>
<tr>
<th>Accident Cause</th>
<th>Objects</th>
<th>Levels (Values)</th>
</tr>
</thead>
</table>
| Inadequate Signal Timing at unsignalized Intersections | Value of average lane volume of left turning vehicles on opposing leg | • Less than 50 vph  
• Between 50 and 100 vph  
• Between 100 and 200 vph  
• Between 200 and 300 vph  
• Greater than 300 vph |
|                                     | Value of average lane volume of offending through movement             | • Less than 200 vph  
• Between 200 and 400 vph  
• Between 400 and 800 vph  
• Between 800 and 1200 vph  
• Greater than 1200 vph |
| Slippery Surface                    | Drainage Condition                                                     | • Excellent  
• Good  
• Adequate  
• Poor  
• Very Poor |
|                                     | Pavement condition                                                     | • Excellent  
• Good  
• Adequate  
• Poor  
• Very Poor |
| Large number of right turn vehicles | Volume of right vehicles                                               | • Less than 100 vph  
• Between 100 and 300 vph  
• Between 300 and 500 vph  
• Between 500 and 800 vph  
• Greater than 800 vph |
|                                     | Curb radius of the right turn movement                                 | • Less than 5m  
• Between 5 and 8m  
• Between 8 and 15m  
• Between 15 and 25m  
• Greater than 25m |

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Figure 5.5 A Typical Comdale/X Screen
The Diagnosis Phase

5.1.5.5 Uncertainty Handling

When an accident prone location is diagnosed, some uncertainty exists as to whether the evidence and hypotheses are true or false. To handle the uncertainty, the system uses a simple probability rule suggested by Mendehall (1981), and Spring (1988):

\[ P(C) = \sum P(E_i) \times P(C|E_i) \]  

(5.1)

Where \( P(C) \) is the probability of a given cause, \( C \), being true (degree of belief in the cause) and \( P(E_i) \) is the probability of the piece of evidence, \( E_i \), being present while \( P(C|E_i) \) is the probability of the cause, \( C \), given the particular piece of evidence, \( E_i \).

The value of \( P(E_i) \) is obtained using the analyst response to the question regarding the piece of evidence \( E_i \). For each piece of evidence five values are presented ranging from \( E_i = 1 \) (not present) to \( E_i = 5 \) (present). \( P(E_i) \) is then taken to equal \( E_i / 5 \).

The importance of each piece of evidence, \( I_i \), is assigned by the experts on a scale from 0 to 1. The value of \( P(C|E_i) \) is calculated as:

\[ P(C|E_i) = I_i / \sum I_i \]  

(5.2)

The degree of belief in countermeasures is calculated in much the same way as in equation 5.1. However, the final degree of belief in a countermeasure is calculated by multiplying the probability of the countermeasure, \( P(Cm) \), obtained from the equation by the importance of the pattern which the countermeasure is to correct. The importance of a pattern is a function of the degree of over-representation of the pattern (see Chapter 4). Figure 5.6 illustrates this function.
Figure 5.6 Pattern Importance as a Function of Pattern Over-representation
5.5.1.5 System Output

The system produces two output files for each analysis. The first, the ".sav" file, contains a record of questions asked and responses given by the user during the analysis. The second, the ".out" file, contains main output statistics produced by the system. These statistics include:

1. Over-represented patterns examined
2. Causes instantiated and their degree of belief
3. Countermeasures suggested and their degree of belief

An example of both files is given in Appendix C.

5.5.2 Verification and Validation

A very crucial task in the development of any knowledge-based system is the verification and validation of the system. If the system is not carefully verified and validated, it may make wrong or inappropriate decisions, which if relied upon, can cause considerable damage.

Verification is defined as "the demonstration of the consistency, completeness and correctness of the system" (Adrion et al., 1982). In other words, verification simply means building the system right. Its goal is to eliminate errors in the system, and to make sure that it corresponds to specifications. Validation, on the other hand, focuses on the quality of the decisions made by the system. It simply means building the right system.
The Diagnosis Phase

(O'Keefe et al., 1987). Adrion et al. (1982) defines validation as "the determination of the correctness of the system with respect to the user needs and requirements".

The methods used to verify and validate expert systems are significantly different from those used for conventional systems. Three main characteristics of expert systems clearly demonstrate this difference (O'Keefe and O'Leary 1993):

First, expert systems employ both numeric and symbolic information (as opposed to numeric information only). Consequently, techniques which are used to verify and validate numeric information may be inapplicable to expert systems. The output of conventional systems is usually a quantitative value which can be compared against an actual observation, while in case of expert systems, there is often no simple wrong or right answer.

Secondly, expert systems are usually developed in an evolutionary or exploratory manner. The development starts with a prototype which is then gradually expanded until it is capable of performing at an acceptable level. Knowing the position of verification and validation in the system life cycle may be a problem.

Thirdly, Expert systems are usually developed for problems which are poorly understood and ill-structured. And thus, defining performance criteria for the system can be a difficult task.

5.5.2.1 Verification

In experts systems, efforts are mainly directed to verify the knowledge base. There are two reasons for this focus. First, the acquisition and representation of knowledge can be
viewed as specific tasks, and therefore, the knowledge itself needs to be verified irrespective of any coding or implementation. Secondly, in case of using expert system shells to build the system, the inference engine and other facilities are supposed to have already been verified by the shell developer.

The verification of the system described here in is based upon detecting anomalies in the knowledge base as described in Nguyen et al. (1990), and Preece et al. (1992). The following are examples of the criteria used for the verification process:

**Correctness** assures that the basic structure of the knowledge base is not violated. Examples for this violations are conflicting rules, subsumed rules (more than one rule have the same conclusion but one contains additional constraints), and circular rules.

**Consistency** assures that the same object or attributes are always called by the same name. This is very important since human have the tendency to misspell names or call the same item by different names. The easiest method to check for consistency is by establishing list of objects and attributes and check for their occurrence. For example, if the object Traffic_Control appears 100 times and the object Traffic_Controls appears once. This means that either Traffic_Controls is a misspelling or it is a rare used object.

**Completeness**: anomalies which can be identified include unreferenced premises and conclusions, dead-end conclusions, and unreachable premises.

Comdale\X also has several debugging features that help detecting different anomalies in the knowledge base. For example, the "Rule Trace" allows the developer to see different rules as the system fires them. It shows which line is being executed and the degree of certainty in the triplet being evaluated. Another very useful feature is the "Watch
Variable" which allows to monitor the status of different keyword-triplets during the inference process.

5.5.2.2 Validation

There are several methods for expert systems validation which vary from the simple ones such as using test cases and sensitivity analysis to the more sophisticated such as using simulation and statistical techniques. The choice of the appropriate validation method depends on factors such as; the type of the problem handled by the system, the availability of human experts, case studies, time and money, and the development stage of the system.

Using test cases is the present predominant method for expert systems validation (O'leary, 1991). In this approach, test cases are presented to both experts and the system and the results are compared. The expert system validity is judged by the number of agreements between experts and the system. This assumes that human experts results are the correct ones (this assumption, obviously, may not be perfectly valid since human experts are subjected to error). Two main guidelines are important in the selection of test cases. First, they should reflect the problems which the system is likely to encounter. Second, they should have enough variation to test different parameters in the system. Although using a large number of test cases can achieve this variety, the number of cases is not the main issue but rather the degree with which they cover different system parameters.

For the system described here in, ten test cases were selected for the validation process. The reason for selecting only ten cases is attributed to the limited time available for the safety expert to perform the validation. Due to data limitations, All cases were intersections (signalized), and they were all in the South Coast Region of the Province
(the Lower Mainland). The ten test cases were solved by both the system and a safety expert who is responsible for performing highway safety improvement programs in the Ministry of Transportation and Highways. The system results were then shown to the expert, who was asked to assess the agreement between his results and those of the system. The fact that the expert solved the test cases before seeing the results of the system is very important to eliminate any bias. The expert was asked to select one of five agreement scales: Perfect Agreement, Strong Agreement, Fair Agreement, Slight Agreement, and No Agreement. In determining a rating for the agreement between the system results and the expert's, two factors were considered: whether the causes and countermeasures were correctly identified by the system and the corresponding degree of belief associated with each correctly identified cause or countermeasure.

Table 5.4 shows a summary of the validation results. Out of the ten cases, one Perfect Agreement, five Strong Agreements, and four Fair Agreements were obtained. There were no conflicts between the expert and the system results. This indicates that, generally, the system results are sound and agree with the expert's results. Only in one test case the expert identified a countermeasure which is not in the knowledge base. The case related to a shopping center near an intersection where merging and diverging traffic caused many rear-end conflicts. One of the countermeasures recommended by the expert was to restrict access. After discussing the location analysis with the expert, it was found that the Highway Planning Branch of the Ministry has just released a draft document titled "Access Management Program Policy" which includes many useful rules for access management. Incorporating some of these rules in the system should enhance the system performance related to similar situations.
<table>
<thead>
<tr>
<th>Location</th>
<th>System Causes</th>
<th>Expert Causes</th>
<th>Countermearures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Route 7 &amp; Harris Rd.</td>
<td>Excessive speed</td>
<td>Enforce speed limit</td>
<td>Install advance warning signs (100%)</td>
</tr>
<tr>
<td></td>
<td>Inadequate signal timing</td>
<td>Retime signals</td>
<td>Increase amber phase (95%)</td>
</tr>
<tr>
<td>Route 99A and 80th Ave.</td>
<td>Inadequate signal visibility</td>
<td>Improve drainage or pavement surface</td>
<td>Reduce and enforce speed limit (70%)</td>
</tr>
<tr>
<td></td>
<td>Inadequate signal timing</td>
<td>Increase amber phase (95%)</td>
<td>Provide sufficient all red phase (51%)</td>
</tr>
<tr>
<td>Route 99A and 96th Ave crosses</td>
<td>Difficulty in visibility</td>
<td>Install warning signs</td>
<td>Increase amber phase (95%)</td>
</tr>
<tr>
<td></td>
<td>Excessive speed</td>
<td>Install advance warning signs</td>
<td>Increase amber phase (95%)</td>
</tr>
<tr>
<td></td>
<td>Slippery/low friction surface</td>
<td>Improve drainage or pavement surface</td>
<td>Reduce and enforce speed limit (70%)</td>
</tr>
<tr>
<td></td>
<td>Inadequate warning signs</td>
<td>Increase amber phase (95%)</td>
<td>Provide sufficient all red phase (51%)</td>
</tr>
</tbody>
</table>

Table 5.4 Comparison Between the System and the Experts Results
Table 5.4 Comparison Between the System and the Experts Results (Cont.)

<table>
<thead>
<tr>
<th>Location</th>
<th>Experts</th>
<th>System</th>
<th>Degree of agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Causes</td>
<td>Countermeasures</td>
<td>Causes</td>
</tr>
<tr>
<td>Route 7 and West Rd.</td>
<td>• Excessive speed</td>
<td>• Provide advance warning signs</td>
<td>• Excessive speed</td>
</tr>
<tr>
<td></td>
<td>• Poor signal visibility</td>
<td>• Realignment of the intersection</td>
<td>• Inadequate warning signs</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Enforce speed limit</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Increase amber phase</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Inadequate signal timing</td>
<td>• Increase all red phase</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Excessive speed</td>
<td>• Provide warning signs</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Insufficient warning</td>
<td>• Enforce speed limit</td>
<td></td>
</tr>
<tr>
<td></td>
<td>signs</td>
<td>• Increase amber phase</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Provide warning signs</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Enforce speed limit</td>
<td></td>
</tr>
<tr>
<td>Carvolth Rd. and</td>
<td>• Inadequate signal timing</td>
<td>• Increase amber phase</td>
<td>• Excessive speed</td>
</tr>
<tr>
<td>200th St. Crosses</td>
<td>• Excessive speed</td>
<td>• Increase all red phase</td>
<td>• Inadequate warning signs</td>
</tr>
<tr>
<td></td>
<td>• Insufficient warning</td>
<td>• Provide warning signs</td>
<td>• Inadequate signal timing</td>
</tr>
<tr>
<td></td>
<td>signs</td>
<td>• Enforce speed limit</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Increase amber phase</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Provide warning signs</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Enforce speed limit</td>
<td></td>
</tr>
</tbody>
</table>
Table 5.4 Comparison Between the System and the Experts Results (Cont.)

<table>
<thead>
<tr>
<th>Location</th>
<th>Experts Causes</th>
<th>Experts Countermeasures</th>
<th>System Causes</th>
<th>System Countermeasures</th>
<th>Degree of agreement</th>
</tr>
</thead>
</table>
| Route 7 & 216th Crosses   | - Poor visibility of signals  
                          - Excessive speed                                                                | - Reduce speed limit  
                          - Relocated advance warning signs                                                | - Poor signal visibility  
                          - Inadequate warning signs  
                          - Excessive speed                                                               | - Relocate advance warning signs (100%)  
                          - Install signals with Backboard and reflective border (75%)                  | Fair Agreement          |
| Route 1A and 152nd Crosses| - Inadequate signal timing  
                          - Poor visibility  
                          - Excessive speed                                                                | - Increase amber/all red phases  
                          - Retime signals  
                          - Reduce speed limit  
                          - Relocate advance warning signs                                                | - Excessive speed  
                          - Inadequate signal timing  
                          - Poor signal visibility                                                      | - Provide 3 signal heads (73%)  
                          - Reduce speed limit (68%)  
                          - Provide sufficient all red phase                                              | Fair Agreement          |
| Route 1A & 140th St.      | - Poor signal visibility  
                          - Slippery pavement                                                               | - Install advance warning signs  
                          - Provide slippery when wet signs  
                          - Overlay pavement surface                                                      | - Inadequate warning signs  
                          - Poor signal visibility  
                          - Slippery pavement                                                             | - Install warning signs (100%)  
                          - Provide slippery when wet sign (56%)  
                          - Overlay/groove existing pavement (56%)                                        | Perfect agreement       |
Table 5.4 Comparison Between the System and the Experts Results (Cont.)

<table>
<thead>
<tr>
<th>Location</th>
<th>Experts</th>
<th>System</th>
<th>Degree of agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Causes</td>
<td>Countermeasures</td>
<td>Causes</td>
</tr>
<tr>
<td>Route 99A and 88th Ave. Crosses</td>
<td>• Inadequate signal timing</td>
<td>• Increase amber phase</td>
<td>• Inadequate signal timing</td>
</tr>
<tr>
<td></td>
<td>• Poor signals visibility</td>
<td>• Install advance timing</td>
<td>• Poor signals visibility</td>
</tr>
<tr>
<td></td>
<td>• Excessive speed</td>
<td>• Reduce/Enforce speed limit</td>
<td>• Excessive speed</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Provide advance warning signs</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Enforce speed limit</td>
<td></td>
</tr>
<tr>
<td></td>
<td>* not in the countermeasures database.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Newton Rd. &amp; 72nd Crosses</td>
<td>• Access conflicts*</td>
<td>• Restrict access*</td>
<td>Slippery pavement</td>
</tr>
<tr>
<td></td>
<td>• Poor signals visibility</td>
<td>• Provide advance warning signs</td>
<td>Inadequate warning signs</td>
</tr>
<tr>
<td></td>
<td>• Excessive speed</td>
<td>• Enforce speed limit</td>
<td>Excessive speed</td>
</tr>
<tr>
<td></td>
<td>• Slippery pavement</td>
<td>• Provide adequate drainage</td>
<td></td>
</tr>
</tbody>
</table>
In sum, with the limited degree of validation work completed, the results are encouraging. A strong degree of agreement exists between the results produced by the system and the recommendations of the experts. However, because of the limited number of cases tested, and the fact that they were confined to urban environment, more validation work is required. Furthermore, most of the locations studied had similar over-represented patterns (Rear-end, Left turn opposing, Right angle and wet weather). It would be valuable to test locations with other accident patterns.

5.6 Conclusion

This chapter described a prototype knowledge-based system for the diagnosis of accident prone locations and the recommendation of applicable countermeasures. The problem of accident prone locations analysis has several characteristics which make it well-suited to the expert system approach. The system is not intended to eliminate or replace the safety analyst but rather as an aid to alert him to possible causes and effective countermeasures. The system is linked to the accident database directly and makes use of the information available in the detection phase to facilitate the diagnosis process. The system utilized two sources for knowledge acquisition: technical literature and interviews with domain experts. The system output includes the over-represented patterns examined, causes instantiated and the suggested countermeasures and their degree of belief. The system was verified by checking for anomalies in the knowledge base to ensure that they do not exist. System validation was carried out by comparing the system results for ten test cases with
the results provided by an expert. A strong agreement was found between the expert and the system results.
6.1 THE REMEDY PHASE

The output of the diagnosis phase is a list of countermeasures that have the potential to reduce the number and/or severity of accidents at each accident prone location. However, before implementing these countermeasures, their economic feasibility must be demonstrated. The objective of the remedy phase is to perform an economic analysis in order to assess the effectiveness of the suggested countermeasures. The main goal of the analysis is to select the most effective countermeasure, or set of countermeasures, for each location and establish which locations should be treated first (i.e., establish funding priorities).

As discussed in Chapter 2, procedures for performing this economic analysis are straightforward and are well-documented in the literature (see, for example, Campbell and Humphrey, 1988; and Laughland et al., 1975). However, there are problems in the way most road agencies estimate the safety benefits of countermeasures which is a crucial step in any of these procedures. The objective of this Chapter is to discuss these problems and to offer methods to overcome them.

6.1.1 Problems With Estimating Safety Benefits Of Countermeasures

The safety benefits of countermeasures are represented by the expected reduction in the number and/or severity of accidents following their implementation. Accident reduction
is calculated as the product of the countermeasure effectiveness by the number of accidents. There are problems with estimating these values. These problems include: system-wide versus project-level analysis, and dealing with uncertainties.

6.1.1.1 System-Wide Versus Project-Level Analysis

A very important step in estimating accident reduction is determining the effectiveness of countermeasures or what are known in the literature as Accident Reduction (AR) factors. Several Agencies such as the U.S. Federal Highway Administration and the Institute of Transportation Engineers have developed AR factors for different countermeasures on a system-wide basis. These values are commonly expressed as a percentage reduction in the total number of accidents. These AR factors are usually used by practitioners at project-level analyses (e.g., in analyzing projects as part of safety improvement programs). There are two problems in using these values to perform project level analysis. First, accident patterns and geometric configuration varies greatly among sites. And therefore, AR factors should vary with site characteristics. Secondly, each countermeasure affect specific accident types and may have no affects on others. Representing countermeasure effectiveness as a percentage of the total number of accidents will obviously lead to very crude results.

To avoid these weaknesses, an extensive literature review was conducted on the relationships between countermeasures effectiveness, specific accident types, accident severities and site characteristics. Particular emphasis was given to recent studies (the last 8 years) and to those which employed sound statistical techniques (e.g. considering regression to the mean effect) as opposed to simple before and after studies. A database is to be developed containing percentage change in accidents related to different accident types, severities and site characteristics.
When estimating the effectiveness of a particular countermeasure for a particular site, the user query the database for studies dealing with similar situations. Usually, more than one study will exist with varying results. In this case, three values are calculated for each countermeasure, an optimistic value, a pessimistic value and a likely value. The average and variance of the countermeasure effectiveness on a specific accident type can then be calculated assuming a Beta distribution as:

\[ AR = \frac{a+4m+b}{6} \]  

(6.1)

\[ VAR(AR) = \left( \frac{b-a}{6} \right)^2 \]  

(6.2)

where

- \( a \) = optimistic expected accident reduction
- \( m \) = likely expected accident reduction
- \( b \) = pessimistic expected accident reduction

These mean and variance are used in the calculation of safety benefits as will be described in the following section.

6.1.1.2 Handling Uncertainty

Both the countermeasure effectiveness and the number of affected accidents are subjected to significant amount of uncertainty. Therefore, any sound economic analysis which include these variables should incorporate some way of uncertainty handling. Unfortunately, a review of current literature indicated that uncertainty is ignored in the
majority of the studies directed at estimating safety benefits of countermeasures. This is very disturbing given the randomness inherited in accidents occurrence.

There are three main sources of uncertainty in the process of estimating safety benefits of countermeasures:

1. uncertainty in the applicability of the countermeasure
2. uncertainty in the effectiveness of the countermeasure
3. uncertainty in the number of accidents affected by the countermeasure

The first two sources of uncertainty are related to the countermeasure applicability and effectiveness. The first term can simply be represented from the countermeasure degree of belief obtained from the output of the diagnosis phase (Chapter 5). The second term can be obtained from Equations 6.1 and 6.2 as described in the previous section.

The number of accidents affected by the countermeasure is also highly uncertain. First, there is less than perfect knowledge about what types of accidents are affected by a countermeasure. For example, improving road lighting by adding light posts will reduce night accidents but may increase fixed object accidents. Some of these relations were investigated in the literature which can provide some estimate of the uncertainty. Another source of uncertainty in the number of affected accidents is the fluctuation in accidents occurrence because of their random nature. This fluctuation may lead to the number of accidents occurring during a certain period being abnormally high or low compared with the normal accident figure at the site. Therefore, the true mean accident number at a site should be estimated. Several techniques (e.g. Empirical Bayes) have been devised to estimate the true mean and the variance of the number of accidents at a site (see Chapters 2 and 3).
The Remedy Phase

The moment analysis approach (Benjamin and Cornell 1970, Ang and Tang 1975, Russell and Ranasinghe 1992) can be used to calculate the final cost effectiveness value and its uncertainty.
7.1 SUMMARY AND CONCLUSION

Given the increasing social and economic costs of road accidents and the lack of efficient methods to analyze accident data, there is a recognized need to develop better methodologies for accident data analysis. Most of the recent accident research has focused on enhancing the statistical techniques to identify accident prone locations and predict accident occurrence. Less attention has been given to improve our understanding of accident contributing factors, patterns and their relation to safety countermeasures. Normally, there is enough data in most accident databases to allow for better understanding of the many factors which contribute to accidents. The problem, however, is the lack of efficient methods to analyze this data. The main reason for the lack of such methods is the complexity of the problem. There are many attributes to this complexity. For example, the complex interaction between accident factors, the uncertainty and fuzziness accompanying them, and the nature of accident data which in many cases are uncertain, unreliable and even conflicting.

This thesis described an expert system approach for carrying out highway safety improvement programs. The objective of the system is to provide highway safety officials with an efficient and reliable tool to identify accident prone locations and then quickly and reliably advise on the appropriate countermeasure(s) based on an analysis of the accident and roadway environment data. The main advantage of the system is its ability
Conclusions and Recommendations

to process a large amount of accident data, separating locations which are most promising
to be treated by engineering measures and providing advice on the countermeasures and
their expected effectiveness. The system also provides an enhancement to many of the
techniques currently used in highway safety improvement programs including two new
methods for identifying accident prone locations. The system consists of three basic
phases which follow the main components of any highway safety improvement program:
*Detection, Diagnosis*, and *Remedy*. The thesis described the development of the
detection and the diagnosis phases and provided a discussion on the issues which may
arise during the development of the remedy phase.

The following four items represent the main contributions of this research:

1. **The Traditional Black Spot program was modified to consider accident correctability by road improvements.** Traditional methods of identifying accident prone locations or black spots, make no distinction between accidents which occur due to road and non-road related factors. Combining accidents that are treatable and non-treatable by road improvements can be misleading and may consequently lead to missallocation of funds by road authorities. In the modified black spot program, a location must exhibit a significant number of *correctable* (i.e., road related) accidents in order to be identified as accident prone. The procedure involves three steps. First, using a fuzzy pattern recognition algorithm to classify accidents in the three highway system categories: the road, the driver, and the vehicle. Secondly, redefining accident frequency and rate to consider accident correctability by road improvements. And finally, using the Empirical Bayes technique to identify accident prone locations.
The modified black spot program has been tested, using data from the Province of British Columbia, Ministry of Transportation and Highways. The results have been presented in a series of graphs, comparing the traditional method and modified method of identifying accident prone locations. The results indicated that the modified method has two main benefits over the traditional approach. First, only road related accidents are considered, resulting in a fewer number of accident prone locations. This will increase the potential effectiveness of safety improvement projects, by limiting the list of accident prone locations and eliminating those which are not treatable by road improvements. A traditional accident prone location is not guaranteed to exhibit a recognizable pattern of accidents for which an engineered solution can be readily found. However, an accident prone location identified by the modified method, on the other hand, is guaranteed to show some pattern of accidents for which at least one predetermined countermeasure can be proposed. Secondly, the ranking of accident prone locations will be prioritized according to each location degree of "proneness" for accidents. This is extremely important in situations when the road authority has resources to address only a limited number of black spots, it is important to focus on those with the highest potential of accident reduction. The output of the modified black spot program can also be useful in assessing the principle of forgiving highways using the average membership of accidents at a site in the road environment group to represent the degree of forgiveness.

2. Extending the definition of accident prone locations by examining not only accident measures but also their patterns. The second component of the detection phase is a new method called the countermeasure-based approach which argues that a given number of accidents with well-defined accident patterns can be treated more effectively than a larger number of accidents with poorly-defined patterns. Traditional
approaches start with a problem (high accident occurrence) and attempt to find solutions (countermeasures). The countermeasure-based approach reverses the traditional process by first identifying main accident patterns that can be targeted by specific countermeasures and then searching for locations which have over-representation of these patterns. The need for such an approach arises from the fact that many locations may have a relatively low frequency of accidents to normally be identified by the black spot programs, but may be effectively treatable by engineering countermeasures because of their well defined accident patterns. The over-representation of particular accident type is assessed by the ratio of the number of particular accident type to the total number of accidents at the location. To account for the random variation in this ratio, the approach utilized the Empirical Bayes technique.

The method was applied to the data set consisting of all signalized intersections in the South Coast Region of the province of British Columbia using accident data from 1989 to 1991. As an illustration, two accident types were considered; right angle accidents, and left turn opposing accidents. Identified accident prone locations of these accident types were compared with those identified by the traditional black spot program. Many locations identified by the countermeasure-based program were not accident prone according to the traditional black spot program even though they had a very high ratio of particular accident patterns. This indicates the usefulness of the approach. The fact that locations identified in this program have a clearly over-represented accident patterns, should facilitate the diagnosis of their safety problems and improve chances of getting better return for the money spent in highway safety improvement programs.
3. The development of a knowledge-based system to analyze accident prone locations. A prototype knowledge-based system to perform accident prone locations analysis was developed in the diagnosis phase. It is shown that the knowledge-based approach best-suits the diagnosis process since it involves a great deal of judgment and experience by the safety engineer. Knowledge-based expert systems provide a means to incorporate experts' knowledge, experience, judgments and other historical information into one system which can be used to aid and guide safety practitioners. There has been previous efforts to develop knowledge-based systems to perform accident prone locations analysis. However, the system described in this thesis differs in three aspects. First, The system is not intended to eliminate or replace the safety analyst but rather as an aid to alert him to possible contributing factors and effective countermeasures. Consequently, the system can cover more aspects of safety analysis. Secondly, the diagnosis process is linked to the accident database directly. This serves two goals: 1) a first pass can be made automatically and without any human intervention through accident records at an accident prone location to produce summary information (accident chain events; apparent contributing factors, etc.). This would relieve the analyst from performing these routine tasks, and 2) assess the uncertainty of the information provided in the accident database by performing logic checks and weighing the credibility of conflicting information. This task may be extremely difficult for an analyst; a typical accident prone location may have more than a hundred accidents to analyze, each with more than 70 items of information. Thirdly, the diagnosis process is directly tied to the detection process. It makes use of the information available from the detection process to facilitate the diagnosis. The system results were verified and validated using ten case studies with satisfactory results.
Conclusions and Recommendations

4. Problems with estimating safety benefits of countermeasures. The thesis outlined two common problems in the way most road agencies estimate the safety benefits of countermeasures: system-wide versus project level analysis and handling uncertainty. Solutions were suggested to both problems.

Another significant outcome of this research was the insight gained at the information included in the accident database. During the development of the modified black spot program (Chapter 3), different variables included in the accident database and their reporting levels were examined in detail. Variables were classified into four types: accident characteristics, driver characteristics, vehicle characteristics, and accident contributing factors or causes. The analysis involved selecting a certain variable and then finding other variables that may in someway provide definition to the first variable and then comparing variable levels.

The analysis indicated that variable levels reported by the police with the least reliability were primary accident occurrence, accident chain events and roadway character. The most reliably reported variables were those concerned with accident date and time, number and sex of drivers, number of vehicles, speed zones, road type, and traffic control. The analysis also indicated that the overall accuracy of police in reporting accident contributing factors was low.

Based on this analysis, revisions were suggested to the MV104 report form. The revisions were accepted by the Motor Vehicle Branch of the B.C. Ministry of Transportation and Highways (the custodian of the MV104 report form) and were used in the development of a new accident report form (MV6020) which is expected to be in use by January 1996.
Also, definitions for several variables which were found to be somewhat confusing to the police were provided. These definitions will be included in the Manual "Accident Reporting Practice in B.C." which is used by police officers in reporting accidents. The definitions included variables such as Accident Location, Direction of Travel, Road Class, Primary Accident Occurrence, and Accident Chain Events.

7.2 RECOMMENDATIONS FOR FURTHER IMPROVEMENTS

This section presents a series of improvements which can enhance and strengthen the methodologies described in this thesis. These improvements reflect some of the system limitations which need to be refined.

7.2.1 The Fuzzy Pattern Recognition Algorithm

In the modified black spot program described in Chapter Three, a fuzzy K-NN algorithm was used for classifying accidents into the three highway system components. While the K-NN algorithm is less computationally intensive and gave satisfactory results, it may be of interest to consider other algorithms especially those which allow for non additivity. Sugeno (1974) suggested using the concept of fuzzy measures, another mathematical expression of fuzziness in contrast to fuzzy sets. The advantage of using fuzzy measures is that it is not required that the measure of the entire domain of discourse be one. Relaxing the additivity condition leads to more flexibility and better applicability to ambiguous situations. As mentioned before, the problem with Sugeno's approach is its computational intensity which makes it difficult to adopt to large scale classification
problems. Recently, there have been efforts to develop simpler classification algorithms based on possibility measures where it is not required that the measure of the universe be unity (see for example Keller and Yan, 1992). Therefore, an investigation of the feasibility of using other non-additive classification algorithms in the detection phase is required.

7.2.2 The Variables Used in the Pattern Recognition Algorithm

The variables selected to classify accidents in the fuzzy pattern recognition algorithm came directly from the accident database which was the only data source available at the time. Recently, however, the B.C. Ministry of Transportation and Highways has established a direct link between the accident database and a road features inventory (RFI) database, thus making more variables available. The RFI variables cover more aspects of the road environment such as shoulder width and type, roadside features, actual degree of curvature, pavement maintenance record etc. Including some of these variables in the classification process may enhance its accuracy. A study of the effect of these variables may be worthwhile.

7.2.3 Validation of the Knowledge Base for the Diagnosis Phase

This is an area that surely needs further work. The knowledge-based system validation was confined to only ten test cases. All the cases were of the same type (signalized) and from the same urban environment (the Lower Mainland). Consequently, they did not have enough variation to adequately test different parameters in the model. Although the
results of the validation were very encouraging, the system performance in other situations should be assessed. Since it is hard to imagine that the system knowledge base is complete, the results of further validation is likely to identify gaps in the knowledge base which should be filled. More work is also needed on the validation of the importance of each piece of evidence assigned by the expert. A sensitivity analysis of the results to these importance weights may be necessary.

7.2.4 Improving the knowledge-based System User Interface

Although the general impression of the analysts who used the system is that it is easy to use, there are two main criticisms. The first is concerned with the lack of the ability to go back and change answers. Once an answer is selected, it can not be changed until the end of the run. The second criticism is that some questions require judgment on the part of the analyst. Therefore, it may be necessary to refine some of the questions and range of answers. It is agreed that improvements to the user interface should be undertaken before a wide use of the system.

7.2.5 Traffic Conflict Techniques

An important research project would be to assess the applicability of the procedures developed in this thesis to traffic conflicts data. As mentioned previously, traffic accidents represent situations in which the whole road system has failed, yet our understanding of the failure mechanism is poor which reduces our ability to better understand safety problems. Because of well-recognized quality and statistical problems with accident records, the observation of traffic conflicts has been advocated as a
procedure to study traffic accidents failure mechanism from a somewhat broader prospective than accident data alone (Brown, 1991; Sayed et al., 1994). However, the focus of most traffic conflicts research has been on the validity of the traffic conflict techniques as surrogates for accidents and different measures of traffic conflicts. Less attention has been given to traffic conflicts as a detection and diagnostic tool. Therefore, developing analytical procedures for traffic conflict data would be of great interest. It is hoped that the methodologies developed in this thesis can serve as a basis for establishing procedures for traffic conflicts analysis.
REFERENCES


References


National Research Council (1990) "Highway safety literature", Transportation Research Board, Washington, DC.


References


Traffic Injury Research Foundation (TIRF), (1993). "Development of an integrated traffic collision data management system in British Columbia, Ottawa, Ontario


### Police Department ACN Prefixes

**R** Royal Canadian Mounted Police

**V** Victoria City Police

**B** Oak Bay Municipal Police

**S** Sarnia Municipal Police

**E** Esquimalt Municipal Police

**C** Central Saanich Municipal Police

**A** Vancouver City Police

**W** West Vancouver Municipal Police

**N** New Westminster City Police

**P** Port Moody City Police

**D** Delta Municipal Police

**M** Matsqui Municipal Police

**T** Nelson City Police

**H** B.C. Highway Patrol

**F** Ports Canada Police

**K** Canadian Forces Military Police

**X** Municipal Forces: Non-Attended

### Jurisdiction Codes

<table>
<thead>
<tr>
<th>Code</th>
<th>Province/Territory</th>
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</thead>
<tbody>
<tr>
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<td>Maryland</td>
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<tr>
<td>AB</td>
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### Vehicle Damage Severity Codes

- 00: No Damage
- 01: Light Damage
- 02: Moderate Damage
- 03: Severe Damage
- 81: Demolished

### Vehicle Type - All Terrain Vehicles

<table>
<thead>
<tr>
<th>Code</th>
<th>Type</th>
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<tbody>
<tr>
<td>00</td>
<td>Snow Mobile</td>
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<tr>
<td>01</td>
<td>Dune Buggy</td>
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<tr>
<td>02</td>
<td>Trail Bike</td>
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<tr>
<td>03</td>
<td>Mini Bike</td>
</tr>
<tr>
<td>04</td>
<td>Swamp Buggy</td>
</tr>
<tr>
<td>05</td>
<td>Hovercraft</td>
</tr>
<tr>
<td>06</td>
<td>Four-Wheel Drive Vehicle</td>
</tr>
<tr>
<td>07</td>
<td>All-Terrain Cycle</td>
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</table>

### Vehicle Use - Dangeroous Goods

<table>
<thead>
<tr>
<th>Code</th>
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<tbody>
<tr>
<td>21</td>
<td>Class 1: Explosives</td>
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<tr>
<td>22</td>
<td>Class 2: Gases</td>
</tr>
<tr>
<td>23</td>
<td>Class 3: Flammable Liquids</td>
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<td>Class 4: Flammable Solids</td>
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<tr>
<td>25</td>
<td>Class 5: Oxidizing Substances</td>
</tr>
<tr>
<td>26</td>
<td>Class 6: Poisonous &amp; Infectious Substances</td>
</tr>
<tr>
<td>27</td>
<td>Class 7: Radioactive Materials</td>
</tr>
<tr>
<td>28</td>
<td>Class 8: Corrosive Substances</td>
</tr>
<tr>
<td>29</td>
<td>Class 9: Miscellaneous Dangerous Goods</td>
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</tbody>
</table>

### Colour Table Following Codes Will Be Used by Police Based Upon CPC

<table>
<thead>
<tr>
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<tr>
<td>RED</td>
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<td>Gold</td>
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<td>Cpr</td>
<td>Copper</td>
</tr>
<tr>
<td>Trq</td>
<td>Turquoise</td>
</tr>
</tbody>
</table>

**Important Note:**

- When estimating repair costs, it should be kept in mind that the amount should reflect what the cost would be if the work is done by a commercial vehicle repair service. Age of vehicle should not be a governing factor.
- In determining repair costs, vehicles with code 81 (Dune Buggy) and 82 (Trail Bike) should not be worked on by non-professionals.
- When estimating repair costs, ensure that the cost will reflect what it would take for a professional to complete the work.
- When estimating repair costs, ensure that the cost will reflect what it would take for a professional to complete the work.
APPENDIX B: FUZZY PATTERN RECOGNITION ALGORITHM

/*HAS146: PROCEDURE OPTIONS(MAIN) REORDER;*/

/**********************************************************************
This program copies an accident data file, calculating and inserting
causal factors on all Page 1 records. The causal factors, or weights,
apportion the blame for the accident out to each of the Driver,
Vehicle and Road.

The weights are stored in the accident record as 2 digit percentages.
In the unlikely event that a percentage is greater than 99.5, it will
be reduced to 99.

A fuzzy pattern recognition algorithm is used. This program is based
upon a C++ program written by Tarek Sayed.

Terminology:
----------
Observation
- a set of 20 variables derived from an accident record.

Label
- the three causal factor weights Wd, Wv, and Wr (in that order).

Labelled Observation
- an observation with a known label (weights) appended.

Unlabelled Observation
- an observation without a label
- the data derived from the accident we want to calculate weights for.

Summary
-------

A file of 1000 Labelled Observations was created by Walid Abdelwahab, David Lee
and Tarek Sayed. The 20 variables were defined from the accident
data, then the weights were assigned manually.
For the candidate accident, (unlabelled observation), the 20 variables are defined, then the observation is compared to all of the Labelled Observations. The K Labelled Observations which match the Unlabelled Observation most closely are found, then the weights of those observations are used to determine the weights for the accident.

***********************************************************************
* CHANGE LOG ***********************************************************************

DATE | WHO | DESCRIPTION
-----------------------------------
94/03/30 | MN | Written by Matthew Nicoll, Cypher Consulting
| | adapted from a C++ program written by Tarek Sayed.

="/*----- Declare the array bounds ------------------------------------------*/

DCL ( nmax INIT(1000), /* max number of labelled observations */
nvar INIT(20), /* number of accident variables */
nvar3 INIT(23), /* nvar + 3 (for the three weights) */
k INIT(20) /* number of 'nearest' observations to use */
) FIXED BIN(15);

DCL ( i, /* row (observation) index for LBL */
 n, /* number of labelled observations in LBL */
j, /* variable number, or col # of LBL, obs */
iw,
p, /* index of the 'nearest' arrays */
percent(3) /* weights converted to integer percentages */
) FIXED BIN(15);

DCL ( nr_inacc,na_inacc, /* record and accident counters */
nr_outacc,na_outacc ) FIXED BIN(31);

DCL ( lbl(nmax,nvar3), /* labelled data: last 3 cols are wts. */
obs(nvar), /* the observation to be labelled */
/* i.e. 1 accident reduced to NVAR variables */
W(3), /* the 3 weights to be calculated for obs */
x,

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d, /* a distance */
sum1,sum2,
maxv,minv,rangev,
max_col(nvar),min_col(nvar),range(nvar)
) FLOAT BIN;

DCL linear(k) FIXED BIN(15); /* pointers to nearest labelled observations */
DCL dnear(k) FLOAT BIN; /* distance of nearest labelled observations */
DCL maxdist FLOAT BIN; /* largest of dnear */
DCL pmaxdist FIXED BIN(15); /* maxdist = dnear(pmaxdist) */

DCL c_contrad(100) CHAR(2); /* contributing factor rank table */
DCL l_contrad(100) FIXED BIN(15);
dcl n_contrad FIXED BIN(15);

DCL accrec CHAR(256); /* accident record */
DCL (page_no CHAR(1) POS(1),
accWd PIC'99' POS(34), /* overlay weights on the */
accWv PIC'99' POS(36), /* old ACCASCON field */
accWr PIC'99' POS(38)) DEF(accrec);

DCL eof BIT(1);
%INCLUDE THASLOG; /* define TRUE and FALSE */

DCL (MAX,MIN,ROUND) BUILTIN; /* functions and subroutines */
DCL THASEOB EXTERNAL ENTRY; /* Extract Observation */

/**************************** Declare Files *******************************

DCL labeld FILE INPUT STREAM; /* labelled data file */
DCL cfrank FILE INPUT SEQUENTIAL RECORD; /* contrib. factor table */
DCL inacc FILE INPUT SEQUENTIAL RECORD; /* input accident file */
DCL outacc FILE OUTPUT SEQUENTIAL RECORD; /* output accident file */

ON ENDFILE(labelled) eof = TRUE;
ON ENDFILE(cfrank) eof = TRUE;
ON ENDFILE(inacc) eof = TRUE;
/*-------------------- START OF EXECUTABLE CODE ------------------------*/

/*---------- Read the labelled observations ------------------------*/

OPENFILE(labelled);
eof = FALSE;

DO i = 1 TO nmax UNTIL(eof);
   GET LIST( (lbl(i,j) DO j=1 TO nvar3) );
   n=i;
END;
IF eof THEN n = n-1;

CLOSEFILE(labelled);

/*---------- Read the contributing factor table ------------------------*/

OPENFILE(cfrank);
eof = FALSE;

DO i = 1 TO 100 UNTIL(eof);
   GET EDIT(c_contrb(i),i_contrb(i)) (COL(1),A(2),X(1),P(2));
   n_contrb = i;
END;

n_contrb = n_contrb - 1;

CLOSEFILE(cfrank);

/*-------- Obtain the min, max and range of each column of labeled data --------*/

DO j = 1 TO nvar;
   minv=1000.;
   maxv=0;
   DO i = 1 TO n;
      minv = MIN(minv,lbl(i,j));
      maxv = MAX(maxv,lbl(i,j));
   END;
   min_col(j)=minv;
   max_col(j)=maxv;
   range(j) = maxv-minv;
END;

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/*---------------- Normalize the labeled data ----------------*/

DO j = 1 TO nvar;
    minv = min_col(j);
    rangev = range(j);
    DO i = 1 TO n;
       lbl(i,j) = (lbl(i,j)-minv)/rangev;
    END;
END;

/*---------------- Open the input and output accident data files, 
then read each accident, calculate the causal factors (weights), 
insert them into the accident record, and write the record out. ----------------*/

OPEN FILE(inacc), FILE(outacc);

eof = false;
READ FILE(inacc) INTO(accrec); /* read the first accident record */

DO WHILE (*eof);
    nr_inacc = nr_inacc+1;

    DO WHILE(page_no #='1'); /* flush non-page accidents */
       WRITE FILE(outacc) FROM(accrec);
       nr_outacc=nr_outacc+1;
       READ FILE(inacc) INTO(accrec);
       nr_inacc = nr_inacc+1;
    END;

    na_inacc = na_inacc+1;

    /*--- Extract the observation variables from the accident record ---*/

    CALL THASEOB (acrec, c_constrb,i_constrb,n_constrb, obs);

    /*--- Normalize the observation ---------------------------*/

    DO j = 1 TO nvar;
       obs(j)=(obs(j)-min_col(j))/range(j);
    END;
Find the 'distance' of the observation from each labelled observation. Compile a list (pointer and distance) of the K nearest labelled observations.

(Use i to point to a row in lbl, p to point into nearest arrays.

/*-----------------------------*/

/*---------- Load up the first k labelled observations ----------*/
maxdist = 0.;
DO i = 1 TO k;       /* (i = p in this loop) */
    inear(i) = i;
    d = distance(obs, lbl(i, *), nvar);
    dnear(i) = d;
    IF d > maxdist THEN DO;
        maxdist = d;
        pmaxdist = i;
    END;
END;

/*------ Now search the rest of the labelled observations ------*/

DO i = k+1 TO n;
    d = distance(obs, lbl(i, *), nvar);
    IF d < maxdist THEN DO;
        dnear(pmaxdist) = d;        /* replace the maximum distance */
        inear(pmaxdist) = i;        /* and the pointer to its */
                          /* related labelled observation */
        maxdist = d;
        pmaxdist = i;
    END;
END;

END;
/*---------- Calculate the three weights ---------------*/

DO iw = 1 TO 3;
    j = var + iw;     /* point to the column in lbl for weight(iw) */
    sum1, sum2 = 0;
    DO p = 1 TO k;    /* for all the nearest labelled observations */
        d = dnear(p);    /* get the distance */
        i = linear(p);   /* get pointer to row in lbl */
        IF d > 0. THEN DO;
            x = (1. / (d * d));
            sum1 = sum1 + (lbl(i, j) * x);
            sum2 = sum2 + x;
        END;
    END;
    W(iw) = sum1 / sum2;
END;

/*---------------- Normalize the weights ----------------*/

sum1 = W(1) + W(2) + W(3);
W(1) = W(1) / sum1;
W(2) = W(2) / sum1;
W(3) = W(3) / sum1;

/*---- Convert to percentages, and put into the accident record ----*/

DO iw = 1 TO 3;
    percent(iw) = ROUND(W(iw) * 100., 0);
    IF percent(iw) = 100 THEN percent(iw) = 99; /* just in case! */
END;

accWd = percent(1);
accWv = percent(2);
accWr = percent(3);

/*----- Write out the accident record ---------------------*/

WRITE FILE(outacc) FROM(accrec);
nr_outacc = nr_outacc + 1;
a_outacc = a_outacc + 1;
PUT SKIP EDIT(na_outacc, W(1), W(2), W(3), accWd, accWv, accWr)
    (F(6), X(2), (3) (F(7,3)), X(2), (3) (A(2), A(1)));
READ FILE(inacc) INTO(accrec); /* read the next accident record */

END;

CLOSE FILE(outacc);

PUT SKIP(2) EDIT('=== PROGRAM THAS140 SUMMARY ===') (COL(20),A);
PUT SKIP(3);
CALL THASPRC('INACC ',nr_inacc,na_inacc,
              'ACCIDENT RECORDS READ. ')
CALL THASPRC('OUTACC ',nr_outacc,na_outacc,
              'ACCIDENT RECORDS WRITTEN.')
Function DISTANCE returns the 'distance' between observations
a and b. Both observations must have nvar variables.

```haskell
distance: PROCEDURE(a,b,nvar)RETURNS(FLOAT BIN);

DCL (a(*),b(*)) FLOAT BIN;
DCL nvar FIXED BIN(15);
DCL j FIXED BIN(15);
DCL (d,x) FLOAT BIN;
DCL SQRT BUILTIN;

d=0;
DO j = 1 TO nvar;
    x = a(j)-b(j);
    d = d + x*x;
END;

d = SQRT(d);
RETURN(d); END distance;

END THAS14O;
THASEOB: PROCEDURE(ACCREC,C_CONTRB,I_CONTRB,N_CONTRB,OBS)REORDER;
```

Extract 20 observation variables from the accident record ACCREC,
for use in the fuzzy recognition algorithm.

See main program THAS14O for details.

C_CONTRB and I_CONTRB constitute a conversion table for converting
the character CONTRBnn variables from the accident record into
the integer variables of the output observation.
DATE | WHO | DESCRIPTION

94/03/29 | MN | Written by Matthew Nicoll, Cypher Consulting
adapted from a C++ program written by Tarek Sayed.

DCL ACCREC CHAR(256); /* input accident record */
DCL C_CONTRB(*) CHAR(2); /* contributing factor codes */
DCL L_CONTRB(*) FIXED BIN(15); /* corresponding integer codes */
DCL N_CONTRB FIXED BIN(15); /* # elements in c_* and l_* */
DCL OBS(*) FIXED BIN(15); /* observation to fill and return */

DCL 1 ACCIDENT_STRUCTURE DEF(ACCREC), /* overlay the structure */
%INCLUDE THASRACD; /* defines individual fields */

DCL (NV,
  NKILLED, /* number of vehicles */
  NINJ, /* TOTALKLD */
  I
  ) FIXED BIN(15);

DCL (SUBSTR,ONSOURCE) BUILTIN;

ON CONVERSION ONSOURCE() = '000'; /* in case of invalid fields */

/*--- Translate the accident variables into an 'observation' ---*/

SELECT(ROADCURV);
  WHEN('1') I = 1;
  WHEN('2') I = 2;
  OTHERWISE I = 3;
END;
OBS(1) = I;

SELECT(WEATHER);
  WHEN('1') I=1; /* CLEAR-CLOUDY */
  WHEN('2') I=1;
  WHEN('3') I=2; /* RAINING */
  WHEN('4') I=4; /* SNOWING-HAIL */
  WHEN('5') I=4;
  OTHERWISE I=3; /* SMOG FOG */
END;

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OBS(2) = I;

SELECT(LANDUSE);
WHEN('6') I=1; /* UNDEVELOPED-AGRICULTURE */
WHEN('7') I=2; /* RURAL RESIDENTIAL */
WHEN('8') I=2;
WHEN('1') I=3; /* URBAN RESIDENTIAL */
WHEN('2') I=3;
WHEN('3') I=3;
WHEN('4') I=4; /* CBD */
OTHERWISE I=0; /* NONE OF THE ABOVE */
END;

OBS(3) = I;

SELECT(ROADGRAD); /* ROADGRAD */
WHEN('1') I=1; /* FLAT */
WHEN('2') I=2; /* GRADE */
WHEN('3') I=3;
OTHERWISE I=4; /* CREST OR SAG HILL */
END;

OBS(4) = I;

SELECT(ROADSURF);
WHEN('1') I=1; /* DRY */
WHEN('2') I=2; /* WET */
WHEN('4') I=0;
OTHERWISE I=3; /* ICE-SNOW */
END;

OBS(5) = I;

SELECT(SPEEDLIM);
WHEN('1') I=1;
WHEN('2') I=1;
WHEN('3') I=1;
WHEN('4') I=1;
WHEN('5') I=1;
WHEN('6') I=1;
WHEN('7') I=2;
WHEN('8') I=2;
WHEN('9') I=3;
WHEN('A') I=3;
WHEN('B') I=3;
OTHERWISE I=0;
END;
OBS(6) = I;

SELECT(TRAPCNTL);
WHEN('01') I=2; /* NONE */
OTHERWISE I=1; /* YRS */
END;
OBS(7) = I;

SELECT(LIGHTING);
WHEN('1') I=1; /* DAYLIGHT */
WHEN('4') I=2; /* DARK-FULL ILLUMINATION */
WHEN('6') I=3; /* DARK SOME ILLUM */
WHEN('2') I=3;
WHEN('3') I=3;
WHEN('5') I=4; /* DARK-NO ILLUM */
OTHERWISE I=0;
END;
OBS(8) = I;

SELECT(LOCN_TYPE); /* location type */
WHEN('01') I=1; /* AT INTERSECTION */
WHEN('03') I=1;
OTHERWISE I=2; /* NO INTERSECTION */
END;
OBS(9) = I;

SELECT(VICTIM_TABLE(1).SAFQUIP); /* safety equipment */
WHEN('1') I=3; /* VEHICLE NOT EQUIPED */
WHEN('2') I=2; /* REST NOT USED */
WHEN('8') I=0;
WHEN('9') I=0;
OTHERWISE I=1; /* RESTRAINING-DEVICE USED */
END;
OBS(10) = I;

SELECT(SUBSTR(ACCHOUR,1,2)); /* time */
WHEN('07') I=2; /* rush hours */
WHEN('08') I=2;
WHEN('09') I=2;
WHEN('12') I=2;
WHEN('13') I=2;  
WHEN('16') I=2;  
WHEN('17') I=2;  
WHEN('18') I=2;  
OTHERWISE I=1;  
END;  
OBS(11) = I;  
/*--- Convert number of vehicles to integer ----*/  
NV = TOTALVEH;  /* convert from character to integer */  
/*---- vehicle type -----*/  
SELECT;  
WHEN (NV = 1 & VEHTYPE1='01') I=1;  
WHEN (NV > 1 & VEHTYPE1='01' & VEHTYPE2='01') I=1;  
WHEN (VEHTYPE1='51' | VEHTYPE1='50' | VEHTYPE1='52') I=0;  
WHEN (VEHTYPE2='51' | VEHTYPE1='50' | VEHTYPE1='52') I=0;  
WHEN (VEHTYPE1='02' | VEHTYPE1='20' | VEHTYPE1='30') I=2;  
WHEN (VEHTYPE2='02' | VEHTYPE2='20' | VEHTYPE2='30') I=2;  
OTHERWISE I=3;  
END;  
OBS(12)=I;  
/*---------- Accident Type ---------------*/  
SELECT;  
WHEN (NV = 1) SELECT;  
WHEN (TYPE2ND1='20' | TYPE2ND1='21' | TYPE2ND1='22') I=1;  
WHEN (TYPE2ND1='23' | TYPE2ND1='24' | TYPE2ND1='24') I=1;  
WHEN (TYPE2ND1='25' | TYPE2ND1='26' | TYPE2ND1='27') I=1;  
OTHERWISE I=2;  
END;  
WHEN (NV > 1) SELECT;  
WHEN (DIAGRAM=2) I=3;  
WHEN (DIAGRAM=1) I=4;  
OTHERWISE I=5;  
END;  
OTHERWISE I=2;  
END;
OBS(13)=I;

 /**<--- Severity. First convert to integers ---*/

NKILLED = TOTALKLD;
NINJ = TOTALINJ;

SELECT;
    WHEN (NKILLED > 0) I=3;
    WHEN (NINJ > 0) I=2;
    OTHERWISE   I=1;
END;
OBS(14)=I;    /* Severity */

Look up the ranking for contributing factors on the provided table

OBS(15) = LOOKUP(CONTRB11);
OBS(16) = LOOKUP(CONTRB12);
OBS(17) = LOOKUP(CONTRB13);
OBS(18) = LOOKUP(CONTRB21);
OBS(19) = LOOKUP(CONTRB22);
OBS(20) = LOOKUP(CONTRB23);

/*==================================================================
   Internal function to look up a contributing factor code on the
code-to-rank translation table.
==================================================================*/

LOOKUP: PROCEDURE(CONTRIB) RETURNS(FIXED BIN(15));
DCL CONTRIB CHAR(2);    /* code to look up */

DCL J FIXED BIN(15);
DO J = 1 TO N_CONTRB;
    IF C_CONTRB(J) = CONTRIB THEN RETURN(I_CONTRB(J));
END;
J=0;
RETURN(J);
END;

This is a research version of THAS140.

A single value of K is entered, and specifications for varying N.
NC is also entered. The LAST NC observations are calculated each time. Nmax and NC must not sum to more than 995.
The SAME observations are calculated each time.

This so that the the dependence of K upon N can be shown.

The calculated weights are then compared to the weights read.

See THAS140 for more information.

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% CHANGE LOG %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

DATE  WHO  DESCRIPTION
+----+
94/04/14  MN  Written by Matthew Nicoll, Cypher Consulting

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

/*-------------- Outer block for getting array bounds etc ---------------*/

/*------ Declare the array bounds ------------------------------------*/

DCL ( nvar INIT(20),          /* number of accident variables */
     nvar3 INIT(23)         /* nvar + 3 (for the three weights) */
 ) FIXED BIN(15);

DCL ( N,                      /* number of labelled observations to use */
     NC,                      /* number more to read and calculate */
     i,j,
     ...);
ntotal,
k,N1,dN,N2        /* number of 'nearest' observations to use  */
)FIXED BIN(15);

DCL (lbl(1000,nvar3),/* labelled data: last 3 cols are wts.   */
maxv,minv,rangev,
max_col(nvar),min_col(nvar),range(nvar)
) FLOAT BIN;

DCL c_constrb(100) CHAR(2);    /* contributing factor rank table */
DCL i_constrb(100) FIXED BIN(15);
dcl n_constrb FIXED BIN(15);

DCL eof BIT(1);
%INCLUDE THASLOG;    /* define TRUE and FALSE */

DCL (MAX,MIN,SQRT) BUILTIN;    /* functions and subroutines */

/**************************** Declare Files ****************************/

DCL labeled FILE INPUT STREAM;    /* labelled data file */
DCL cfrank FILE INPUT STREAM;    /* contrib. factor table */

ON ENDFILE(labeld) eof = TRUE;
ON ENDFILE(cfrank) eof = TRUE;

PUT SKIPLIST('Enter N1, dN, N2: ');
GET LIST(N1, DN, N2);
PUT SKIPLIST('Enter NC (number to calculate), and K') (A);
GET LIST(NC, k);
PUT SKIP DATA (N1, DN, N2);
PUT SKIP DATA(NC, K);

/**************************** Read the contributing factor table ***************************/

OPEN FILE(cfrank);
eof = FALSE;

DO i = 1 TO 100 UNTIL(eof);
    GET FILE(cfrank) EDIT(c_constrb(i),i_constrb(i))
         (COL(1),A(2),X(1),F(2));
n_contrb = i;
END;
n_contrb = n_contrb - 1;
CLOSE FILE(cfrank);
/* PUT SKIP LIST(n_contrb,' contributing factor ranks read in.'); */

/*--------- Read the labelled observations ------------------------*/

OPEN FILE(labeld);
.eof = FALSE;

DO i=1 TO 1000 UNTIL(eof);
   GET FILE(labeld) LIST( (lbl(i,j) DO j=1 TO nvar3) );
   n=i;
END;
ntotal=n-1;
CLOSE FILE(labeld);

;/*---- Obtain the min, max and range of each column of labeled data ----*/

DO j = 1 TO nvar;
   minv=1000.;
   maxv=0;
   DO i = 1 TO ntotal;
      minv = MIN(minv,lbl(i,j));
      maxv = MAX(maxv,lbl(i,j));
   END;
   min_col(j)=minv;
   max_col(j)=maxv;
   range(j) = maxv-minv;

   IF minv = maxv THEN DO;
      PUT SKIP DATA(j,minv,maxv);
      PUT SKIP LIST('No variation in variable in labelled data.',
                     'Increase N and try again');
      STOP;
   END;
END;

;/*------------- Normalize the ALL labeled data ---------------*/
DO j = 1 TO nvar;
    minv = min_col(j);
    rangev = range(j);
    DO i = 1 TO ntotal;
        lbl(i,j) = (lbl(i,j) - minv) / rangev;
    END;
END;

PUT SKIP LIST(ntotal,' labelled observations read in and normalized.');

PUT SKIP LIST (' K    N    NC    Ebar    SD');

/**=============  INNER BLOCK: N-LOOP  ==============================*/

DO n = n1 TO n2 BY dn;
BEGIN;

DCL (i, j, iw, ic, first)
    /* row (observation) index for LBL, */
    /* variable number, or col # of LBL, obs */
    ) FIXED BIN(15);

DCL (obs(nvar),
    /* the observation to be labelled */
    /* i.e. 1 accident reduced to NVAR variables */
    W(3),
    /* the 3 weights to be calculated for obs */
    Wn(3),
    /* 3 weights assigned manually to the obs */
    E(NC), Esum,
    /* error for each obs, sum of same */
    sum, x, Ebar, SD
    ) FLOAT BIN;

DCL (THASSOB,
    /* Extract Observation */
    THASKNR
    /* calc weights from K nearest */
    ) EXTERNAL ENTRY;

/**===================================================================

Calculate the weights for each of the last NC labelled observations
and compare with the provided (manual) weights.
Sum the errors, so that an average error and standard deviation

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can be calculated..

\[ \text{first} = \text{ntotal} - NC + 1; \]

\[ E_{\text{sum}} = 0.; \]
\[ ic = 0; \]
\[ \text{DO } i = \text{first} \text{ TO ntotal}; \]
\[ ic = ic + 1; \]

\[ /*---- Copy form lbl into obs and Wm ---------*/ \]
\[ /*---- (already normalized) \quad \quad \quad */ \]

\[ \text{DO } j = 1 \text{ to nvar}; \]
\[ \quad \text{obs}(j) = \text{lbl}(i,j); \]
\[ \text{END}; \]
\[ \text{DO } iw = 1 \text{ TO 3}; \]
\[ \quad \text{Wm}(iw) = \text{lbl}(i, \text{nvar} + iw); \]
\[ \text{END}; \]

\[ /* \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad */ \]

\[ \text{Calculate the weights for the unlabelled observation} \]
\[ \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad */ \]

\[ \text{CALL THASENR}(k, \text{lbl}, n, \text{obs}, \text{nvar}, W); \]

\[ \quad \text{sum} = 0.; \]
\[ \quad \text{DO } iw = 1 \text{ TO 3}; \]
\[ \quad \quad x = W(iw) - \text{Wm}(iw); \]
\[ \quad \quad \text{sum} = \text{sum} + x^2; \]
\[ \text{END}; \]
\[ \quad E(ic) = \text{SQRT}(\text{sum}); \quad \quad /* \text{error} */ \]
\[ \quad E_{\text{sum}} = E_{\text{sum}} + E(ic); \quad \quad /* \text{sum of all errors} */ \]

\[ /* \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad */ \]

\[ \quad \text{PUT SKIP EDIT}(\text{Wm}, W, E) ((2) ((3) (F(5, 3), X(2))), X(2), F(5, 3)); */ \]

\[ \text{END}; /* \text{do} */ \]
\[ E_{\text{bar}} = E_{\text{sum}} / NC; \]

\[ \text{sum} = 0.; \quad \quad /* \text{standard deviation} */ \]
DO i = 1 TO NC;
    x = (E(i) - Ebar);
    sum = sum + x*x;
END;
SD = sum/NC;

PUT SKIP EDIT (k,N,NC,Ebar,SD) ((3)(F(5)), (2)( x(2),F(6,4) ) );

END; /* begin block */
END; /* k-loop */

END THAS141;
APPENDIX C: SAMPLE DIAGNOSIS SESSION

********** Begin Save Session **********

At what distance along the main road does the intercession first appear?
Between 100m and 200m

To what degree are warning signs visible to drivers?
Barely

At what distance from the intersection do signals become visible?
Between 50m and 100m

How many primary signal heads are provided?
Two

What are the sizes of the signal lenses?
Three 12inch Lenses

To what extent is conflicting background lighting a problem?
Not a Problem

Does the intersection have a separate left turn lane?
No

What is the approximate average lane volume of left turn vehicles?
Between 50 and 100 vph

What is the approximate average lane volume of the opposing through movement?
Less Than 200

Is there an exclusive left turn phase?
Yes
How effective do signal phasing patterns accommodate existing traffic flows?
Effective

How long is the amber phase provided?
Four Seconds

Is an All-Red Clearance Provided?
Provided But Not Sufficient

How does the average running speed on intersection approaches compare to speed limit?
ARS Greater Than SL

Does the intersection has a separate right turn lane?
Yes

What is the average volume of pedestrians crossing at the intersection?
Between 10 And 25 ped/day

How do you describe the pavement surface of this location?
Adequate

How do you describe the drainage surface of this location?
Good

How do you describe the Lighting at this location?
Good

********** End Save Session **********
APPENDIX D: SAMPLE DIAGNOSIS OUTPUT

ACCIDENT PRONE LOCATIONS ANALYSIS SYSTEM

Analyst Name: Tarek Sayed
Organization: University of British Columbia
Analysis Date: 1994/09/12
Analysis Started at: 14:18:03
Analysis Finished at: 14:23:25

LOCATION CHARACTERISTICS

Segment: 2730
Kilometer: 1.800
Route Description: Hwy 7 & Shaughnessy St.

PREDOMINANT PATTERNS EXAMINED

Rear-end
Wet Weather
Night

CAUSES

<table>
<thead>
<tr>
<th>Causes</th>
<th>Degree of Belief</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inadequate Warning Signs</td>
<td>68%</td>
</tr>
<tr>
<td>Excessive Speed</td>
<td>66%</td>
</tr>
<tr>
<td>Slippery Pavement</td>
<td>53%</td>
</tr>
<tr>
<td>Inadequate Signal Timing</td>
<td>51%</td>
</tr>
<tr>
<td>SUGGESTED COUNTERMEASURES</td>
<td>DEGREE OF BELIEF</td>
</tr>
<tr>
<td>-------------------------------------------------</td>
<td>------------------</td>
</tr>
<tr>
<td>Relocate/Install Warning Signs</td>
<td>80%</td>
</tr>
<tr>
<td>Provide Sufficient All-Red Phase</td>
<td>54%</td>
</tr>
<tr>
<td>Overlay/Groove Existing Pavement</td>
<td>51%</td>
</tr>
<tr>
<td>Provide &quot;Slippery When Wet&quot; Sign</td>
<td>51%</td>
</tr>
</tbody>
</table>