Accurate smooth pursuit eye movements lead to more accurate manual interceptions.

by

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A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Science

in

THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES
(Computer Science)

The University Of British Columbia
(Vancouver)

August 2015

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Abstract

In ball sports, athletes are taught to keep their eyes on the ball to catch or hit it successfully. This intuitive field experience has already been studied in the laboratory, indicating that tracking a moving object with smooth pursuit eye movements enhances our ability to predict the object’s trajectory in time and space. Similarly, intercepting a moving object critically relies on motion prediction. Here we assessed the functional significance of eye movements for manual interceptions.

In a novel paradigm, we asked observers (n=32) to track a small moving dot, back-projected onto a translucent screen, and to intercept it with their index finger in a designated ‘hit zone’. Hereby, only the first part (100-300 ms) of the trajectory was shown. Thus, observers had to extrapolate the trajectory and intercept its assumed position anywhere within the hit zone.

Results show that better pursuit (low eye position and velocity error, high velocity gain, few catch-up saccades of small amplitude) lead to more accurate interceptions. A Hazard analysis yielded two interception strategies: Early interceptors relied on tracking quality and memory feedback given at the end of each trial, while late interceptors depended more on tracking smoothness, small initial saccades, and accurate eye latencies. Early interceptions (less time of invisibility) yielded smaller 2D interception error, while the interception timing was better for longer periods of smooth tracking (later interceptions).

A regression model tree identified low tracking error and small saccadic eye movements as those eye parameters predicting accurate interceptions best. Not only do observers benefit from smooth pursuit eye movements during manual interception, but the interception accuracy also scales with the quality of the eye movements.
Preface

This dissertation is original, unpublished, independent work by the author, Jolande Fooken.

Experiments presented in this thesis were conducted in UBC’s Sensorimotor Systems Laboratory (SSL) and UBC’s Neuroscience of Vision and Action (NOVA) Laboratory, supervised by Prof. Dinesh Pai and Dr. Miriam Spering.

Prof. Dinesh Pai, Dr. Miriam Spering, Dr. Sang-Hoon Yeo, and I were involved in designing and programming all experimental aspects of the presented study. Additionally, I was responsible for data collection, processing, and analysis.


The UBC Behavioural Research Ethics Board approved all procedures related to this work. Ethics board certificate ID: H12-02564.
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Acknowledgments

First of all I would like to thank my supervision team Miriam Spering and Dinesh Pai for their guidance and assistance throughout the last two years. It never ceases to amaze me how both of you manage to come up with the most valuable comments, scientific inspiration, and constructive criticism in between other meetings, teaching sessions, and picking up the kids.

I also would like to thank Paul van Donkelaar for taking the time to read this thesis and especially for coming all the way from the Okanagan to attend the thesis seminar. Your scientific input is greatly appreciated.

Another huge thank you to Terry McKaig who started this cooperation and made this entire project possible. Also, thanks to the UBC Thunderbirds baseball team who were excellent, competitive, and highly motivated participants.

This goes out to my lab: Thank you all for patiently enduring my humming, singing, self-debating, talking, joking, laughing, and cursing over the last couple of years in general and during the last two months in particular. Debanga (our lab dinosaur), Cole (the man for emergencies), Prashant, Edwin, Darcy, and Janick thank you all for your constant support and motivation. Kaity, we have been through most of this together and I will miss having you around to brainstorm, chat, and de-stress over the next few years.

Lastly, I would like to thank my family. Parents, thanks for asking me repeatedly how my vacation was going, while I was sweating over this beast. You have taught me well, especially how to keep up composure and easiness, even when life gets busy. Jan, I can honestly say that this would not have gone as smoothly without you. You introduced me to three whole new (and mostly very productive) hours of the day by getting me out of bed with freshly brewed coffee every morning. Mainly I want to say though - for inspiring me every day - deThankYou.
1 Introduction

In professional baseball, a fastball can be pitched with a velocity of up to 100 mph. Yet, it is possible for batters to ‘get a piece of the ball’. When hitting a home run, the interplay between sensory information (input) and motor action (output) is working at its optimum. However, not only professional athletes are interacting with moving objects in everyday life. We are moving through a dynamically transforming visual environment. The use of visual sensory information and cognitive prediction is required to successfully guide motor commands while interacting with this constantly changing world. This chapter will give an introduction on how the visuomotor system is operating to cope with the complex and constantly changing environment around us. First, the functional properties of different types of eye movements will be discussed in Section 1.1, focusing on saccadic and smooth pursuit eye movements. Next, the visuo-motor coordination will be addressed in section Section 1.2, giving an introduction to visual tracking mechanisms for different motor demands. Finally, section Section 1.3 will give a preview of the research rationale presented in this thesis.

1.1 Types of Eye Movements

When inserting a thin thread into a sewing needle, our fixation system prevents our eyes from actively moving around, to focus the eye of the needle most accurately. So why are we constantly moving our eyes in every day life? The visual environment around us is full of objects of interest and while we pass through this world, neither we nor these objects will remain stationary. Thus, humans use a combination of different kind of eye movements to keep up with the dynamic world around them. In principal, the function of these eye movements is either to
hold the image of interest steady on the retina, or else, to shift the gaze direction of the eye to a new point of interest. Four types of eye movements enable stabilization of the image of the viewed object on the fovea, that is, the retinal region where visual acuity is highest; smooth pursuit eye movements, vergence eye movements (tracking objects in depth), the vestibulo-ocular reflex, and the optokinetic nystagmus. The latter two are evolutionarily older involuntary reflexes. Furthermore, gaze shift or eye reset is accomplished by quick phases of nystagmus or saccadic eye movements. These functionally different types of eye movements complement each other in natural situations (e.g., Heinen & Keller, 2004; Krauzlis, 2004).

In the following, functional and physiological properties of these different types of eye movements will be discussed in more detail. However, this section will focus on voluntary eye movements that primates mainly use when tracking or shifting gaze to objects of interest: saccadic and smooth pursuit eye movements.

### 1.1.1 Saccadic Eye Movements

When looking for Waldo in a busy visual scene of dozens or more people, our eyes search in a series of fixations connected by quick, ballistic eye movements called saccades. Saccades rapidly redirect the fovea from one object of interest towards another and correct for errors between eye and target position (Dodge, 1903; Sparks & Mays, 1990). Visual perception is actively suppressed during these relocations of the fovea, presumably to avoid motion blur (Carpenter, 1988). The distinct velocity profile of a saccade follows a standard waveform consisting of a single smooth increase and decrease (figure 1.1). Saccade peak velocities can be up to 900 deg/s while their duration remains rather short (30-100 ms) (Leigh & Kennard, 2004). Saccades show a consistent relationship between peak velocity and amplitude as well as duration and amplitude, called the main sequence (Becker & Fuchs, 1969; Bahill et al., 1975). As a single saccade is a very short eye movement, it cannot be controlled by visual feedback. Instead, saccades are regulated by an internal feedback loop based on an efference copy of the motor command sent to the motoneurons (Bridgeman, 1995). Remarkably, the latency to initiate a saccade is relatively long with up to 200 ms for unexpected target motion, suggesting that these discrete eye movements are not just a reflex but require significant
Figure 1.1: Exemplary eye position (A) and velocity (B) during a saccade with an amplitude of 9.9°, a peak velocity of 240°/s, and a duration of 100 ms.

preparation by the central nervous system.

1.1.2 Smooth Pursuit Eye Movements

While playing video games such as Pac-Man or Pong we are confronted with targets (i.e. pac man himself or the pong ball) that are constantly in motion. When tracking these moving objects, observers will naturally follow them with smooth pursuit eye movements, a slow rotation of the eyes to compensate for the target’s movement. These continuous eye movements are primarily driven by visual motion (Rashbass, 1961; Lisberger et al., 1987; Robinson, 1965). Smooth pursuit eye movements not only shift the gaze to compensate for the motion of a tracked object, but also hold an object steady on the fovea during slow body motion or head rotation (Ilg, 1997; Carpenter, 1988).

Pursuit eye movements are considerably slower than saccadic eye movements. Human observers are able to track targets moving between 1-100 deg/s (Meyer et al., 1985). However, for target velocities exceeding 30 deg/s pursuit is often not quick enough and will be complemented by so called catch-up saccades (de Brouwer et al., 2002). Thus, a combination of smooth pursuit tracking and catch-up saccades is used to compensate for retinal slip, i.e. the error between eye velocity and target velocity. The appearance of a moving stimulus at 30 deg/s elicits pursuit eye movements with a latency of about 100-150 ms (Carl & Gellman, 1987; Lisberger et al.).
Similarly, an unexpected change in the target’s trajectory would result in an analogous delay (Schwartz & Lisberger [1994]). The magnitude of the pursuit latency depends on visual target properties, such as size and luminance (Tychsen & Lisberger [1986]), as well as predictability of the target trajectory (Bahill & McDonald [1983]). If the future target trajectory is predictable, the oculomotor system will anticipate the specific target trajectory and initiate smooth pursuit even earlier than target onset (see figure 1.2 A) (Kowler [1989], Barnes & Asselman [1991]).

Figure 1.2: Exemplary eye position (A: blue trace) and velocity (B: green trace) compared to target position (grey dashed trace) during smooth pursuit tracking. Here, the oculomotor system predicts the time of target onset. Accordingly, the eyes begin to move prior to the target.

The smooth pursuit response is separated into two intervals: first, the open-loop or initiation phase, and second, the closed-loop or maintenance phase (Lisberger et al., [1987], Tychsen & Lisberger [1986]). The first ∼ 100 ms pursuit eye movements are mainly driven by the visual motion of the target, i.e. the retinal image velocity. During this open-loop phase the eye initially accelerates in the same direction as the target (first 0-20 ms) and later (20-100 ms) adjusts to the target’s velocity (see figure 1.2 B). After this initial phase, visual feedback closes the loop, that is, the difference between eye and target motion is minimized by means of a negative feedback control. This feedback control could either be driven by an efference copy signal from the eye movement and the retinal target motion signal which are then compared to stabilize the image of the target on the retina (Crapse & Sommer [2008]), or by proprioceptive feedback, that is, an afferent feedback from
the stretch receptors in the ocular muscles (Weber & Daroff, 1972). Lisberger et al. (1987) suggested that the continuation of smooth pursuit is attributed to a neural velocity memory that maintains the current speed of the eyes unless visual input provides another command. Ideally, the speed of the eye and pursued target match closely, resulting in a velocity gain, i.e. the ratio of eye relative to target velocity, close to 1. When the tracked target disappears, ongoing pursuit can be maintained, however, at a much lower gain (Becker & Fuchs, 1985; Barnes, 2008). In summary, pursuit is driven by visual motion, a negative feedback signal, predictive mechanisms, and other cognitive mechanisms, such as attention, reward, or anticipation (see Barnes, 2008, for review).

Anatomically, physical inputs of visual motion that arrive on the retina will be processed by retinal ganglion cells. From there, the signal is transmitted to the lateral geniculate nucleus (LGN) and subsequently to the early visual cortical areas (V1). Motion signals are then sent to the middle temporal visual area (MT) and middle superior temporal visual area (MST). These two brain areas are crucial for processing smooth pursuit. MT has been shown to guide pursuit eye move-

![Figure 1.3](image-url)

**Figure 1.3:** Lateral view of the monkey brain. Traditional descending pursuit pathway is indicated. MT/MST: middle temporal/middle superior temporal visual area; FEF: frontal eye fields; PON: pontine nuclei; PMN: brain stem premotor nuclei; VN: vestibular nucleus. (Modified from Krauzlis, 2004)
ments, containing neurons that code for acceleration, speed, and direction of target motion \cite{Lisberger1999} and has also been related to the perception of motion \cite{Newsome1988}. The adjacent area MST has been shown to play an important role in pursuit maintenance \cite{Dursteler1988} and there is evidence that MST neurons also respond to extraretinal (i.e. no image motion on the retina) signals during pursuit \cite{Ilg2008}. Next, the target motion information is passed on to the frontal brain areas, namely the frontal eye field (FEF). Here, initiation and maintenance of pursuit is facilitated. From the FEF, the signal is mediated to the pons of the brainstem, in particular the pontine nuclei (PON), and finally passed on to the cerebellum (compare figure 1.3). From here a motor command is sent to the extraocular muscles to move the eye. This pathway is similar for pursuit and saccadic eye movements. The anatomic substrates of both systems and a detailed discussion of differences and similarities is reviewed elsewhere \cite{Krauzlis2004, Krauzlis2005}.

### 1.1.3 Other Types of Eye Movements

When driving through the prairies of interior Canada, the visual scene becomes rather stationary and simple. Staring out the car window, it seems as if there is no need to voluntarily view any particular point in this endless nothingness. Yet, the observer’s eyes will move in a sawtooth-like pattern. These involuntary eye movements are due to the optokinetic reflex (OKR) which consists of two phases: a slow and continuously following eye movement as well as a fast, discrete resetting of the eye position \cite{Collewijn1969}. This reflex is evoked by the stimulation of a wide visual field, that is, large regions of the viewed image move together. Thus, the OKR is a feedback system, driven by the error between desired (stabilized image on the retina) and actual image speed.

Another type of involuntary eye movements is caused by the vestibulo-ocular reflex (VOR). This reflex is not driven by an external visual scene, but by the vestibular system. It serves to stabilize the image on the retina during head movements \cite{Ilg1997}. The semicircular canals of the inner ear sense the head movement velocity and subsequently conduct the signal to the eye muscles via the vestibular and oculomotor nuclei. For natural head movement velocities the gain of
the VOR is close approximately 0.7, that is, the evoked eye movement counteracts the rotation of the head (Leigh & Zee, 1999).

1.1.4 Vision for Action and Perception

The different types of eye movements previously discussed can be viewed as tools that primates use to navigate through complex visual scenes. However, how do we eventually identify Waldo, or how do we avoid that Pacman is eaten by the ghosts chasing him? The visual information available to us is used to establish a perception of the world around us. Based on earlier work of Mishkin & Ungerleider (1982), Goodale & Milner (1992) proposed two separate cortical pathways for visual processing: The ventral, or vision for perception, stream mediates the perceptual identification and recognition of objects, while the dorsal, or vision for action, stream facilitates the localization and required sensorimotor transformation for visually guided actions (i.e. eye movements) towards those objects. This view of partly independent processing of visual perception and control of motor action has caused controversy in the literature and has been challenged by others (e.g. Franz et al., 2000).

Nonetheless, a strong link between pursuit eye movements and perception has been reported numerous times in many studies (see Spering & Montagnini, 2011, for review). In particular, smooth pursuit eye movements have been reported to enhance perception of moving objects in time (Bennett et al., 2010) and space (Spering et al., 2011). In the former study Bennett et al. (2010) investigated the judgment of the ‘time to contact’ of a moving stimulus to a given spatially fixed target in a pursuit versus fixation condition. They found a perceptual advantage of smooth tracking in this particular time dependent prediction-motion task. Similarly, Spering et al. (2011) introduced a paradigm called ‘eye soccer’, in which the perceptual ability to judge if a visual target (i.e. the ball) would hit or miss a vertical line segment (i.e. the goal) was compared between a fixation and a pursuit condition. Accordingly, subjects either fixated the ball, while the goal was moving towards the fixation point, or they tracked the ball moving towards the stationary goal. In both cases, ball and goal were presented only briefly (100-500 ms). They found that the judgement of ‘hit’ or ‘miss’ trials was more accurate for pursuit than
for fixation trials and thus concluded that pursuit enabled a more precise estimate of the predicted spatial target trajectory.

1.2 Visuo-Motor Coordination

While attempting to kill a spider that is quickly running over the kitchen counter, the brain integrates visual feedback information and prediction of the spider’s path to trigger the deadly slap. However, how are we able to strike at exactly the right time and place? Despite the seeming effortlessness with which the spider’s life is ended, the neural control of this action appears to be rather complex, involving a fine-tuned interplay between visual feedback signals and experience-based predictive signals (Van Donkelaar et al., 1992; Brenner et al., 1998; Brouwer et al., 2002; de Lussanet et al., 2004; Zago et al., 2009; Soechting & Flanders, 2008). The implicit role of eye movements in hand movement tasks, such as hitting, manual tracking, pointing, or intercepting, will be discussed in the following.

1.2.1 Hitting Moving Objects

To successfully intercept a moving target, the hand must meet the object along its natural path. The mapping of the three-dimensional object motion on to the two-dimensional retina represents the so-called inverse problem of vision (Palmer, 1999). Generally, this is an ill-posed problem, that is, one retinal image could be produced by an infinite number of possible real objects. At the same time, a single given object can cause several different retinal images depending on the viewpoint, spatial occlusion, illumination and so on. One theory of how the brain addresses this problem was developed by Gibson (1979) stating that due to physical laws the solution to the inverse problem is constrained in such a way that ecologically impossible solutions become irrelevant. According to Gibson the relevant information would be carried through an optic array, specified by the pattern of light coming from the environment (for a summary see Zago et al., 2009). Later, Lee (1980) advanced Gibson’s idea that information available in the optic flow field is used to control activity, to hypothesize that the visual and motor system are functionally inseparable, being components of a unified perceptuo-motor system. Lee et al. (1983) also revived Gibson’s idea of the optic variable tau (τ), the ra-
tio between image size and its expansion velocity, which approximates the time an approaching object will take to reach the potential catcher or hitter (Lee et al., 1983; Savelsbergh et al., 1991; Brouwer et al., 2003). While some studies suggest that subjects initiate their movement when \( \tau \) reaches a critical value, other studies show shortcomings of the \( \tau \) theory (see Tresilian, 1999, for review). Yet, all of these models share a common approach: Based on a critical time to contact variable, an optimal time to initiate an interceptive motor action to e.g. catch or hit a moving object is identified, while these studies do not address the spatial outcome of the movement.

On the one hand, it has been shown that moving the hand rapidly improves the temporal accuracy when intercepting a moving target (Schmidt, 1969; Newell et al., 1979; Tresilian et al., 2003). On the other hand, quick motor actions reduce the spatial accuracy of the interception (Fitts & Peterson, 1964). This is known as the speed-accuracy trade-off. The spatial and temporal aspects of intercepting moving objects with respect to hand movement characteristics, such as reaction time, velocity, acceleration, or initial path, have been studied extensively. However, fewer studies consider the role of eye movements.

1.2.2 Eye Movements and Manual Interception

Bahill & Laritz (1984) posed the research question ‘why batters can’t keep their eyes on the ball’. They monitored eye movement strategies of graduate students compared to a professional baseball player, when hitting a simulated fast ball (60-100 mph). While the graduate students used different and very inconsistent strategies, such as preliminary head movements and anticipatory saccades of various sizes, the professional baseball player tracked the ball with the same combination of head and eye movements each trial. The reported smooth pursuit tracking velocity of the professional player was significantly higher, enabling the eyes to keep up longer with the simulated target. Similarly, Land & McLeod (2000) conducted a study, in which they compared eye movements in professional and amateur cricket batsmen. They found that batsmen, generally, view the ball closely up to the moment the bowler releases it, then make a predictive saccade to the place where they expect it to bounce of the ground, wait for it to arrive, and sub-
sequently track its trajectory for 100-200 ms after the bounce. Again, they found more consistent strategies in professional batsmen compared to amateurs as well as a shorter latency for the first predictive saccade. Other studies confirm that athletes use a combination of smooth tracking and saccadic eye movements, when hitting or catching balls (Ripoll et al., 1986; McKinney et al., 2010; Land & Furneaux, 1997).

Successfully intercepting a moving object critically relies on the ability to predict the target’s future location. Extrapolation of the target’s path relies on visual information about its location, velocity, and even acceleration (Brouwer et al., 2002; Eggert et al., 2005; Soechting et al., 2009; Port et al., 1997; Delle Monache et al., 2014). Furthermore, experience from previous trials and thereby the use of memory plays an important role in manual interception tasks (Brouwer et al., 2005; Brouwer & Knill, 2007; Issen & Knill, 2012).

Several studies have suggested that smooth pursuit eye movements are beneficial for a successful manual interception. Mrotek (2013) examined the change of smooth pursuit eye movements when intercepting moving targets that underwent speed perturbations at various times. They found a similar response in hand and eye movements: Both, smooth pursuit and finger movement responded more quickly when the target speed perturbation occurred earlier in the trial. Based on their results, they concluded that an active process of visual target path extrapolation guides eye as well as hand movement. In an earlier study, (Mrotek & Soechting, 2007b) examined characteristics of eye-hand coordination in a manual interception task. Here, subjects intercepted a given trajectory by moving their index finger from a fixed starting position at the bottom of the screen along its surface. They were free to initiate the movement at any time. Interestingly, subjects tracked the target’s trajectory right until the point of interception with high-gain smooth pursuit eye movements without being instructed to do so. Furthermore, the probability of catch-up saccades was considerably smaller after onset of the manual interception. Brenner & Smeets (2011) reported that subjects are unable to hold their gaze on a set fixation point just before hitting a moving target, even if they are instructed to do so. All these findings stress the importance of eye movements for successful manual interceptions.
1.3 Linking the Eye to the Hand

As discussed in section 1.1.4, tracking a moving object with smooth pursuit eye movements enhances the observer’s ability to predict its future path. Additionally, observers use smooth tracking eye movements in manual interception tasks without being instructed to do so, indicating that these type of eye movements are advantageous (Mrotek & Soechting, 2007b). Moreover, the opposite approach also holds true: Adding hand tracking to an eye-tracking task, improves eye movement accuracy (Gauthier et al., 1988; Koken & Erkelens, 1992). Thus, a close coupling between eye and hand movement performance seems plausible.

In the past, several studies have addressed this interplay between ocular and manual strategies and performance. However, a shortcoming of these studies is often the unnaturalness of the experimental design and the hand movements in particular. Delle Monache et al. (2014) investigated whether interceptive performance was related to oculomotor behavior. However, the actual task was carried out by moving a virtual baseball player along the horizontal plane of a simulated baseball field by moving a computer mouse. Interception was triggered by button click. Arguably, this task engages the visuo-motor system in a different way than a fully carried out hand movement directed towards the target. Similarly, Brenner & Smeets (2011) used a stylus, which had to be slide across a drawing tablet to intercept the moving target. Even though more extensive hand movements are enabled in this task, the two dimensional restriction within a plane is still unnatural. In a different study Brenner & Smeets (2010) posed the research question: ‘do eye movements matter when intercepting moving objects’. They compared the spatial position of a manual interception between fixation (on a static point) and smooth pursuit (of the moving target) trials. However, subjects were unable to see their hand during movement and received no feedback about their performance, again limiting the applicability. Johansson et al. (2001) looked at eye-hand coordination in a goal-directed bar movement to a target that had to be contacted. Subjects were instructed to grasp the bar at its right end and move it so that the left end made contact with the target. This task was performed with and without obstacles. Subjects fixated on critical points such as the grasp site on the bar, the final target, or the obstacles, rather than the hand or the moving bar. They concluded that the
gaze strategy was linked to hand movement planning by directing the hand to key positions when moving the object to a fixed, stationary target.

In conclusion, a lot of these studies have focused on hand movements rather than on the functional significant of eye movements. This study aims to link the quality of observer’s eye movements to the quality of the interception. Furthermore, eye and hand movement strategies will be identified and again linked to the most important eye movement characteristics.
2 Methods

This chapter introduces a new paradigm to investigate the relationship between eye movements and predictive, intercepting hand movements. Section 2.1 describes the experimental design, specific task, and data collection in detail. Subsequently, the analysis of the collected data is discussed in section 2.2. Section 2.3 summarizes the methodology of different types of data driven computational models.

2.1 Eye-Hand Coordination Task

The core of the experimental methods is a novel paradigm that was developed to explore the coordination of eye and hand movements in greater detail. In particular, subjects were asked to track a small moving dot (the ball) back-projected onto a translucent screen, and to manually intercept its trajectory as accurately as possible in time and space. The ball disappeared after launching and observers were instructed to intercept the ball with their index finger after it would have entered a designated hit zone. Thus, this task requires the ability to extrapolate visual motion trajectories in order to give an accurate motor response.

2.1.1 Participants

32 players (mean age 19.7 ± 1.4 yrs) of the 2013/2014 UBC Thunderbirds varsity baseball team participated in the study. Each player gave written informed consent prior to the experiment. All observers were unaware of the purpose of the experiment. Experiments were in accordance with the principles of the Declaration of Helsinki and approved by the Behavioural Research Ethics Board of the University of British Columbia (ID: H12-02564). Out of the 32 male players, 27 reported
to be right- and 5 to be left-handed. Visual acuity, contrast sensitivity, stereo vision, and color vision were tested with standardized vision tests (Bailey-Lovie high-low visual acuity eye chart, Randot stereo vision test, Ishihara color vision) prior to the experiment. All observers had normal stereo and color vision. Except for two players (visual acuity of 20/32 & 20/25 on the ETDRS acuity chart), all players had normal or better than normal vision. The team average ETDRS score was 20/16 and the contrast sensitivity team average was 20/29.

2.1.2 Visual Stimuli and Apparatus

The stimulus was back-projected using a Vivid LX20 LCD projector (Christie Digital Systems, USA) with a refresh rate of 60 Hz onto a translucent screen that consisted of a non-distorting projection screen material (Twin White Rosco screen for front and rear projection) clamped onto a solid glass plate and fixed in a compact aluminum frame. The displayed window was 48.5 (H) × 38.8 (V) cm in size with a resolution of 1280 (H) × 1024 (V) pixels. Observers were seated in a dimly lit room at 46.25 cm distance from the screen with their head supported by a combined chin- and forehead-rest (see figure 2.1). Observers viewed stimuli binocularly. A magnetic tracker probe was tightly attached to the participant’s index finger (figure 2.1 D). To avoid obstruction, the tracker cable was fixed on a fitted glove.

Figure 2.1: Experimental setup: Stimuli are back-projected onto a compact translucent screen (A) using an LCD projector (B). Participant are seated in reaching distance. The head is supported by a chin and forehead rest (C). The finger tracker probe is tightly attached to the index finger (D) and connected to the trakSTAR™ magnetic tracker (E).
The stimulus display was controlled by the Eyelink® host computer (graphics card: NVIDIA GeForce GT 430) and the experiment was programmed in Matlab 7.1 (Mathworks, Natick, MA) using Psychtoolbox 3.0.8. The ball (black Gaussian dot, SD = 0.38) moved across a gray background equally divided into a lighter (35.87 cd/m²) and darker (31.45 cd/m²) grey zone. The ball’s velocity was set to 3 different speeds (see table 2.1 for details). Participants performed the task with both hands (randomized block order across all players). The ball moved from left to right for right handed trials and from right to left for left handed trials, respectively. The trajectory type (linear and curved) was varied block-wise.

For linear trials, the ball followed a straight path in the horizontal plane \((y = 0)\) with the initial fixation points of \(x = \pm 14^\circ/s\) depending on the motion direction. For curved trials, the initial fixation point remained the same. The subsequent trajectory was simulated to be the parabolic flight of a batted baseball on which three forces act: gravitational force \(F_G\), drag force \(F_D\), and Magnus force \(F_M\) (compare figure 2.2).

**Figure 2.2:** Forces acting on a spinning baseball in flight. The drag force \(F_D\) counteracts the direction of the velocity vector. The Magnus force \(F_M\) acts in the \(\mathbf{\omega} \times \mathbf{v}\) direction with \(\mathbf{\omega}\) denoting the angular velocity of the baseball. The gravitational force \(F_G\) acts downward. Figure from Nathan (2008).
Originally the trajectory of a fly ball was described by Brancazio (1985):

\[ F_D = \frac{1}{2} \rho A C_D v^2 \]  
\[ m\ddot{x} = -F_D \cos(\phi) = F_D \left( \frac{v_x}{v} \right) \]  
\[ m\ddot{y} = -F_D \cos(\phi) - mF_G = F_D \left( \frac{v_y}{v} \right) - mg \]  
\[ \ddot{x} = -\kappa v v_x \]  
\[ \ddot{y} = -\kappa v v_y - g, \]  
where \( \kappa = \rho \frac{AC_D}{2m} \).  

In this equation, \( F_D \) denotes the magnitude of the aerodynamic drag force, \( \rho \) the air density, \( A \) the cross-section of the flying baseball, \( C_D \) the drag coefficient, \( v \) the ball’s velocity, where \( v_x \) and \( v_y \) are the horizontal and vertical component of the velocity vector, respectively, \( \ddot{x} \) and \( \ddot{y} \) the horizontal and vertical acceleration components, \( m \) the mass of the ball, \( \phi \) the angle between the velocity vector and the horizontal component, and \( F_G = g \) the gravitational acceleration of the ball (see table 2.1 for more detail). In addition to the aerodynamic drag force, a baseball will be exposed to the Magnus force which is a result of its spin. A Magnus force \( F_M \) was added to horizontal and vertical accelerations (compare equations 2.7 and 2.8), setting the final path of the simulated curved trajectory to

\[ \ddot{x} = -\frac{1}{m} \left( F_d \cos(\phi) - F_M \cos \left( \phi + \frac{\pi}{2} \right) \right) \]  
\[ \ddot{y} = -\frac{1}{m} \left( F_d \sin(\phi) - F_M \sin \left( \phi + \frac{\pi}{2} \right) \right) \]

where \( F_M = K f v C_D. \)  

Here, \( f \) refers to the frequency with which the simulated ball spins and \( K \) is an empirical constant determined by measurements of a spinning baseball in a wind tunnel by Watts & Ferrer (1987). Note that equation 2.9 only holds for velocities for which the drag coefficient does not vary strongly, that is, for velocities at which a hit fly ball travels (Adair, 2002). Baseball related constants as well as initial conditions used for the simulation are summarized in table 2.1. Figure 2.3 shows
the full trajectories of the simulated fly-balls for the three initial speeds chosen.

Table 2.1: Constant baseball specific properties of simulated fly ball.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air density (20°C. sea level)</td>
<td>( \rho = 1.204 \text{ kg/m}^3 )</td>
<td>ICAO manual</td>
</tr>
<tr>
<td>Baseball cross section</td>
<td>( A = 2\pi \cdot 0.0365 \text{ m}^2 )</td>
<td>Bahill et al. (2005)</td>
</tr>
<tr>
<td>Drag coefficient</td>
<td>( C_D = 0.3 )</td>
<td>NASA research</td>
</tr>
<tr>
<td>Mass of baseball</td>
<td>( m = 0.145 \text{ kg} )</td>
<td>Adair (2002)</td>
</tr>
<tr>
<td>Initial angle of flight</td>
<td>( \phi = 35^\circ )</td>
<td>Adair (2002)</td>
</tr>
<tr>
<td>Gravitational force</td>
<td>( g = 9.81 \text{ m/s}^2 )</td>
<td>System of Units</td>
</tr>
<tr>
<td>Frequency of ball spin</td>
<td>( f = 50 \text{ Hz} )</td>
<td>Adair (2002)</td>
</tr>
<tr>
<td>Empirical constant</td>
<td>( K = 1.2 \cdot 10^{-3} \text{ kg} )</td>
<td>Watts &amp; Ferrer (1987)</td>
</tr>
<tr>
<td>Initial x-y position</td>
<td>([ \pm 14.08^\circ, 0] )</td>
<td>Experimental design</td>
</tr>
<tr>
<td>Initial absolute velocities</td>
<td>24.1, 29.3 or 34.2(^\circ)/s</td>
<td>Experimental design</td>
</tr>
</tbody>
</table>

Figure 2.3: Simulated fly-ball trajectories for three different initial speeds (24.1\(^\circ\)/s, 29.3\(^\circ\)/s, 34.2\(^\circ\)/s) and a constant launch angle (\( \phi = 35^\circ \)).
2.1.3 Experimental Procedure and Design

Each player completed 4 sessions of 2 blocks each, that is, a linear and curved trajectory session with the right and left hand, respectively. At the start of a 2 block session, players did 27 pursuit-only baseline trials and 9 manual interception practice trials with the entire trajectory visible. The sequence of events during the actual experiment is shown in figure 2.4. The task was to predict the path of the ball after it disappeared and to intercept it upon entering a designated hit-zone as accurately as possible in time and space. In a given trial, the trajectory type and interception hand was known, while the ball’s speed and presentation duration were randomly interleaved. Three ball speeds ($24.1^\circ/s$, $29.3^\circ/s$, or $34.2^\circ/s$) and three presentation durations (100 ms, 200 ms, or 300 ms) yielded 9 different conditions. The initial horizontal position of the fixation spot was at $-14^\circ/s$ for right handed trials and at $+14^\circ/s$ for left handed trials, while the vertical position was at $0^\circ/s$. The ball’s motion started upon a successful fixation: The subject had to fixate on the ball within a radius of $<2.8^\circ$ for a randomly chosen time between 500 and 700 ms (drift correction).

![Figure 2.4: Trial sequence for non-practice trials: (A) Initial fixation and eye-tracker drift correction. (B) Upon successful fixation (500-700 ms) ball motion onset either straight (linear block) or parabolic (curved block). (C) Ball disappears after 100, 200, or 300 ms (randomized). (D) Player intercepts at estimated position in darker grey strike zone (red cross) and gets feedback of the actual ball’s position (black dot).](image-url)
2.2 Data Analysis

Data were collected in real time using the Eyelink® tower. Subsequent data analysis was carried out with Matlab 8.3.0.532 (R2014a) and R version 3.2.0 running on Windows 7 Enterprise.

2.2.1 Eye and Hand Movement Recordings and Analysis

Eye position was monitored with a tower-mounted, video-based eye tracker (EyeLink® 1000; SR Research Ltd., Ottawa, Ontario, Canada) and sampled at 1000 Hz. Index finger position was recorded with a magnetic tracker (3D Guidance trakSTAR, Ascension Technology Corporation, Vermont, USA) with a sampling rate of 240 Hz. Eye and finger velocity were obtained by digital differentiation of the respective eye and finger position signals over time. The 2D finger interception position was recorded in x- and y- screen centered coordinates for each trial. Trials in which the point of interception was not detected were excluded due to technical error. Eye movements were analyzed off-line using custom-made routines in Matlab. Eye velocity profiles were filtered using a low-pass, second-order Butterworth filter with cutoff values of 15 Hz (position) and 30 Hz (velocity). In each trace saccades were detected using customized criteria: 5 consecutive frames had to exceed a fixed velocity criterion of target speed ± 50°/s. Precise on- and offsets were then determined by finding the eye acceleration’s (digital differentiation of eye velocity) respective minima and maxima. Saccades were excluded from pursuit analysis. Pursuit onset was detected in individual traces using a piecewise linear function fit to the filtered position trace within a time window between 260 ms before stimulus motion onset and the first saccade onset or 80 ms after stimulus onset, whichever occurred earlier. We calculated the following open-loop pursuit parameters (pursuit onset to 140 ms after pursuit onset): pursuit, initial mean and peak velocity and acceleration. Furthermore, the closed-loop gain (140 ms after pursuit onset to point of interception) and the root mean square eye position and velocity error across the entire trial were determined.

Out of 28556 trials, 243 (0.85%) were excluded due to blinking, 453 (1.59%) were excluded because the final interception position on the screen was not detected and 57 (0.2%) trials were excluded because the subject moved their hand.
2.3 Statistical Methods and Learning

General statistical methods applied to the data set are summarized in section 2.3.1 and 2.3.2. Furthermore, statistical learning is discussed in the following sections. Supervised learning involves building a statistical model for predicting or estimating an output based on one or more input variables. Accordingly, statistical learning techniques were applied to the data set in order to identify the relationship between collected input (eye and finger measures) and output (finger accuracy) data. Models were trained using the data set $D$ of the 32 players described above and evaluated using a test set $\tilde{D}$ of 10 new players collected in 2014 (a year after the original data collection). These statistical models were build in R version 3.2.0.

2.3.1 General Statistical Methods

To flag outliers, a standard score (z Score) analysis was performed on all eye and finger parameters (previously determined in Matlab) across all players and all trials. Trials that deviated from the mean value of each parameter for more than $\pm 3\sigma$ were excluded for further analysis (compare figure ??). Furthermore, effects of target properties (presentation duration, target speed, and trajectory type) as well as player attributes (handedness and batting side) on the dependent variable (interception error) were tested using repeated measures ANOVA. Moreover, the correlation between independent and dependent parameters was analyzed by means of regression analysis.

2.3.2 Hazard Analysis

Traditionally, the hazard analysis is used to assess the risk of a system to become hazardous to the environment (Watson & Leadbetter, 1964). However, this so called survival analysis can generally be used to model any kind of time-to-event critical data. At any given time step a hazard level between 0 (nothing is occurring) and 1 (all occurrences of the given event) can be calculated. In this case, a hazard analysis was conducted to find the critical point of interception for each player individually. The time series from stimulus motion onset to the longest recorded trial
was divided into 50 ms bins. In every time bin the number of executed interceptions was counted across all trials.

![Graph](image)

**Figure 2.5:** Exemplary hazard curve for a single subject. For each time point after stimulus disappearance the hazard level is calculated. Favored interception times for each player can be determined.

Next, the hazard levels in each time interval were calculated for every player (equation 2.10).

\[
H_t = \frac{I_t}{N - \sum_{i=1}^{t} I_i},
\]

(2.10)

where \(H_t\) is the Hazard level at time interval \(t\), \(I_t\) number of interceptions counted during the same time interval \(t\), \(N\) the total number of interceptions made, and \(\sum_{i=1}^{t} I_i\) the number of interceptions that have occurred in all previous time intervals. Time dependent Hazard levels can be plotted for each player and the preferred time of interception can be determined (see figure 2.5).
2.3.3 Attribute Selection

Redundant (highly correlated) eye and finger parameters were identified using the Caret R package that provides a findCorrelation function. This function analyzes a correlations matrix of all attributes (eye and finger) in the given data set. Attributes with an absolute correlation of 0.75 or higher were reduced to one parameter for the subsequent model analysis. These uncorrelated eye and hand movement attributes were then further investigated using the Boruta R package, a feature selection algorithm that aims to identify all relevant attributes (Kursa & Rudnicki, 2010). The algorithm implemented in the Boruta R package is a wrapper built around a random forest regression algorithm (for more detail see Liaw & Wiener, 2002). The method uses an additional randomly designed shadow attribute containing shuffled values of original values across all predictors. Attributes are considered to be relevant if the random forest ranks their importance higher than the shadow attribute.

2.3.4 Regression Techniques

Linear regression is a simple tool for predicting a quantitative response. In particular, a multiple linear regression model will serve as a baseline for relating all predictor variables $X_j$ (eye and finger measures) to the response variable $Y$ (finger accuracy). The multiple linear regression for $p$ distinct predictors takes the form

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \epsilon.$$  

(2.11)

Here, $\beta_0$ is the expected value of $Y$ when $X = 0$ (intercept term), $\beta_j$ quantifies and weights the link between the $j^{th}$ predictor variable and the response, and $\epsilon$ is a mean-zero random error term. The parameters are estimated using a least squares approach: $\beta_0, \beta_1, \ldots, \beta_p$ are chosen to minimize the sum of squared residuals

$$RSS = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2.$$  

(2.12)

$$= \sum_{i=1}^{n} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{1i} - \hat{\beta}_2 x_{2i} - \ldots - \hat{\beta}_p x_{pi})^2,$$  

(2.13)
where the multiple least squares regression coefficient estimates $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_p$ minimize equation \[2.13\] (James et al., 2013).

However, the relationship between a single predictor and the response might not be linear. An extension of the linear regression model is a polynomial regression, that is, the replacement of the linear with a polynomial function. The polynomial regression model output $y_i$ of a single predictor $x_i$ is computed by

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 x_i^3 + \ldots + \beta_d x_i^d + \epsilon_i. \quad (2.14)$$

Here, $\epsilon_i$ is the error term and $d$ is the degree of the polynomial function, for instance $d = 3$ for a cubic regression model. A polynomial regression model fitted to the single best predictor will serve as another baseline model.

### 2.3.5 Regression Tree

In general, a decision tree segments the predictor space by applying a set of optimized splitting rules. One way of visualizing the partitioning of the predictor space is to draw a schematic tree (compare figure 2.6).

**Figure 2.6:** Terminology of a decision tree. First node is called the root. Intermediate nodes are reached based on splitting rules. End nodes (no further splits) are called terminal leafs. A node-system within one branch of the tree is called a subtree.

Generally, a regression tree is built following two basic steps (James et al., 2013):
1. Divide the predictor space, i.e. the set of possible values for predictors $X_1, X_2, ..., X_p$, into $J$ distinct and non-overlapping regions $R_1, R_2, ..., R_J$. These regions take the shape of boxes. The goal is to find boxes that minimizes the sum of squared residuals, given by

$$
\text{RSS} = \sum_{j=1}^{J} \sum_{i \in R_j} (y_i - \hat{y}_{R_j})^2, \tag{2.15}
$$

where $\hat{y}_{R_j}$ is the mean response of the training observations in the $j^{th}$ box. The division of the predictor space is done by recursive binary splitting: This approach begins at the top of the tree where all observations belong to a single region and then successively splits the predictor space on its way down (compare figure 2.7). The tree will grow until a set minimum number of observations is reached in the terminal node.

2. Once the regions $R_1, ..., R_J$ have been created, the same prediction is made for every observation that falls into the specific region. The actual response for a given test observation is predicted using the mean values for the training observations $\hat{y}_{R_j}$ in each $R_j$. 

Figure 2.7: Five-region ($R_1, ..., R_5$) example tree. Recursive binary splitting is done by selecting a predictor variable $X_j$ and a cutpoint $s$ such that the predictor space is split into regions $\{X|X_j \leq s\}$ and $\{X|X_j > s\}$. Splitting rules are chosen such that the resulting tree has the lowest RSS.
An extension to the standard regression tree was developed by Quinlan (1992) who introduced the M5 model tree. This particular method constructs multivariate linear models instead of distinct values at the terminal leaves, equivalent to piecewise linear functions. Later, Wang & Witten (1997) reviewed and revised M5. This model is implemented in the Cubist R function used for regression tree modelling. The tree is constructed through the following steps:

- The initial tree is built using a splitting criterion that investigates the expected error at each node, that is, the standard deviation of each attribute’s values is treated as the measure of error at that node. Accordingly, the attribute chosen at each note, maximizes the standard deviation reduction (SDR) given by

\[
\text{SDR} = sd(y) - \sum_i \frac{|y_i|}{|y|} \times sd(y_i)
\]  

(2.16)

- To avoid overfitting the model is then pruned back into a smaller tree with fewer splits. First, the response values for all training instances are predicted by incoming predictor values at a given node. The absolute difference between these predicted responses and the actual response values is averaged. To prevent underestimation of the expected error, the average is multiplied by an error factor \(\xi\)

\[
\xi = \frac{n + p}{n - p},
\]  

(2.17)

where \(n\) is the number of training instances (attribute values) and \(p\) is the number of predictors that represent the response at the given node.

- A linear regression model (see section 2.3.4) is built at every interior node of the unpruned tree. The regression is fitted using predictor attributes that appear in the subtree below the node of interest. The linear regression models are optimized through dropping predictor terms. Terms are dropped as long as the estimated error calculated using equation 2.17 is minimized. Thereby, the tree is pruned back starting from the terminal leafs until the expected estimated error no longer decreases.

- Next, the model is smoothed to compensate for discontinuities. Starting with
the linear model at the terminal leafs, the predicted values for the response are computed. Then, this predicted value is filtered at each node along its path back to the root. In particular, this smoothing is done by joining the predicted value coming into the node with the prediction made at that node:

$$\rho' = \frac{n\rho + kq}{n+k}, \quad (2.18)$$

where $\rho'$ is the outgoing prediction that is passed up to the next higher node, $\rho$ is the incoming prediction from the node below, $q$ is the value that is predicted by the linear model at this specific node, $n$ the number of training instances and $k$ is a constant with default value 15 (Wang & Witten, 1997).

- Lastly, boosting can be performed. Boosting is a procedure in which several trees are grown sequentially (James et al., 2013). Hereby, the information of each tree is used to grow the next one

$$\hat{f}(x) = \sum_{b=1}^{B} \lambda_b \hat{f}^b(x), \quad (2.19)$$

where $\lambda$ is the shrinkage parameter and $B$ the total number of trees grown.

### 2.3.6 Neural Network

In general, an artificial neural network is a nonlinear statistical model for predicting an output variable based on one or more predictor variables. The central idea of a neural network is to derive features from a given input and subsequently model the response by fitting a nonlinear function of these features. Thus, building a neural network is a two-stage regression model (compare figure 2.8) that can be thought of as an adaptive basis function method. The structure of a feed-forward neural network (also known as multilayer perceptron) leads to a response function of the form (Titterington, 2004)

$$Y = g \left\{ w_{00} + \sum_{j=1}^{M} w_{0j} f \left( w_{j0} + \sum_{k=1}^{p} w_{jk} X_k \right) \right\} + \epsilon. \quad (2.20)$$

Here, $\epsilon$ refers to a Gaussian white noise error term, $w_{00}$ describes the output
bias, $\mathbf{w} := \{w_{jk}\}$ defines the connection weights of input variables $X_1, X_2, \ldots, X_p$ to the hidden nodes $Z_1, Z_2, \ldots, Z_M$ with $w_{j0}$ denoting the bias term of each hidden node, while $w_{0j}$ for $j = 1, \ldots, M$ corresponds to the weight of the connection from the hidden nodes to the output node. The function $g(\cdot)$ specifies the activation function at the output node and is chosen to be the identity function for a continuous response $Y$. The activation functions at each hidden node are defined by $f_k(\cdot)$. Often the neuron activation function is chosen to be sigmoidal, however, for this implementation the activation functions are calculated by $f(v) = (e^{2v} - 1)/(e^{2v} + 1)$.

In practice, the model will be fitted using a training dataset $D$ of $n$ training instances $(Y_i, X_i)$, yielding a likelihood function $p(D|\mathbf{w})$. The problem of learning how to map the structure of the feed forward neural network was addressed by

**Figure 2.8**: Schematic network diagram of a single hidden layer, feed forward neural network. Output $Y$ is predicted by a nonlinear model of derived features $Z_1, \ldots, Z_M$. These features are linear combinations of the input predictors $X_1, \ldots, X_p$ (modified from Hastie et al., 2008).
MacKay (1992) who suggested a Bayesian framework in which the data error is interpreted as a likelihood function and the regularizer corresponds to a prior probability distribution over the weights. The posterior distribution of the likelihood function can be written as

\[ p(w|D, \alpha, \beta) \propto p(w|\alpha) p(D|w, \beta), \]

(2.21)

where \( \alpha \) (regularizing constant) and \( \beta \) (precision constant) are hyperparameters determined by Bayes’ rule (for more detail see MacKay, 1992). The \( \texttt{brnnR} \) package uses this Bayesian regularization approach to fit a two-layered (input and one hidden layer) feed forward neural network to the data set \( D \) (MacKay, 1992; Foresee & Hagan, 1997). Initial weights are assigned using the Nguyen & Widrow (1990) algorithm. This algorithm aims to distribute the active region of each neuron approximately uniform across the layer’s input space. The optimization of the regularization parameters \( \alpha \) and \( \beta \) requires solving the Hessian matrix

\[ H = \beta \nabla^2 E_D + \alpha \nabla^2 E_W, \]

(2.22)

where \( E_D \) is the minimized sum of squared errors between data input and network output during training, and \( E_W \) is the sum of squares of the network weights. For the \( \texttt{brnn} \) neural network Gauss-Newton approximation is performed to compute the Hessian matrix which is done using the Levenberg-Marquardt optimization algorithm (Foresee & Hagan, 1997).

### 2.3.7 Model Evaluation

To compare the different statistical models, the root mean square error (RMSE) will be determined for each approach described above. The better the model fits the data, the smaller the value of the RMSE, which is given by

\[ \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{f}(x_i))^2}, \]

(2.23)

where \( y_i \) is the actual observation in a test set \( \hat{D} \) and \( \hat{f}(x_i) \) the prediction made for the \( i^{th} \) observation. Additionally, the correlation between the actual test val-
ues $y_i$ and the predicted values $\hat{f}(x_i)$ is determined using the Pearson’s correlation coefficient $c$ given by

$$c = \frac{\text{cov}(y, \hat{f})}{\sigma_y \sigma_{\hat{f}}}. \quad (2.24)$$

That is, the covariance of $y$ and $\hat{f}$ divided by their respective standard deviations.
3 Results

In this section the relationship between eye movements and interceptive hand movements will be explored. First, effects of target properties and other external factors will be analyzed. Then, the significance of different eye and finger measures on interception accuracy will be investigated. Next, pursuit quality across all trials and, in particular, over the time course of a single trial will be evaluated. Furthermore, statistical learning models will be applied to the data set. Finally, different interception strategies will be identified and discussed in detail.

3.1 Effects of Target Properties

As described in section 2.1, players performed the interception task for linear and curved trajectories. The mean finger interception error differed in magnitude between these two trajectory types (linear: M = 2.19, SD = 1.51; curved: M = 2.36, SD = 1.39). We found a main effect of the trajectory type on the finger interception error ($F(1,31) = 90.18, p < 0.001$) and subsequently analyzed the two data sets separately. Qualitatively, there was no pronounced difference in relating eye attributes to the finger interception error in later analysis. However, intercepting the curved trajectory was a more complex task of higher variability. Thus, only results from curved trajectory trials will be reported from here on.

Players performed the task with both their hands. The data set was split into *natural* (interception with player’s strong hand) and *unnatural* (interception with player’s weak hand) trials. Subsequently, the means of the interception error of right- and left-handed players were compared for the natural and unnatural case. A two sampled, two-tailed t-Test showed no difference in means between the two groups. Accordingly, data were averaged for all (right- and left-handed) players.
Effects of target properties (presentation duration and target speed) on the interception error, finger latency, and peak velocity are summarized in table 3.1. The target speed had a significant effect on all three finger measures. The target presentation duration had a significant effect on the interception error, but not on the finger latency and peak velocity. The interaction between speed and presentation duration has a significant effect on interception error and finger peak velocity.

Table 3.1: $p$-Values of repeated measures ANOVA for finger attributes, i.e. interception (intercept.) error, finger latency and peak velocity (vel.), with factors speed and presentation duration (pres. dur.).

<table>
<thead>
<tr>
<th>Fing. attribute</th>
<th>Speed F(1,31)</th>
<th>$p$ value</th>
<th>Pres. dur. F(1,31)</th>
<th>$p$ value</th>
<th>Speed × Pres. dur. F(1,31)</th>
<th>$p$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept. error</td>
<td>73.09</td>
<td>&lt; 0.001</td>
<td>491.85</td>
<td>&lt; 0.001</td>
<td>56.68</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Finger latency</td>
<td>123.16</td>
<td>&lt; 0.001</td>
<td>0.85</td>
<td>0.36</td>
<td>2.07</td>
<td>0.15</td>
</tr>
<tr>
<td>Finger peak vel.</td>
<td>579.63</td>
<td>&lt; 0.001</td>
<td>0.52</td>
<td>0.47</td>
<td>31.08</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

Figure 3.1 depicts the mean values of these finger attributes averaged across all players and trials for each of the respective conditions. The interception error shows a speed range effect (3.1 A), that is, the interception error is lowest for the medium target speed (29.3°/s). The effect of target presentation duration can also be seen: The finger error decreases with longer presentation duration.

Figure 3.1: Effect of target properties (presentation duration and speed) on finger attributes. Mean values across all players and trials are plotted for the respective conditions. Finger interception error (A), latency (B) and peak velocity (C) are depicted.
Finger latency and peak velocity mainly depend on target speed. The finger latency decreases with increasing target speed (figure 3.1 B), while the finger peak velocity increases for higher target speed (figure 3.1 C).

Main effects of target properties on selected eye attributes (tracking error, velocity gain, eye peak velocity, and cumulative saccades) are summarized in table 3.2. The target presentation duration and the interaction between target speed and presentation duration have a main effect on all selected eye attributes. The target speed has a main effect on eye velocity gain, peak velocity and cumulative saccades but not on the tracking error.

Table 3.2: p-Values of repeated measures ANOVA for eye attributes, i.e. 2D tracking error, eye velocity gain, peak velocity, and cumulative (cum.) saccades, with factors speed and presentation duration (pres. dur.).

<table>
<thead>
<tr>
<th>Eye attribute</th>
<th>Speed F(1,31)</th>
<th>p value</th>
<th>Pres. dur. F(1,31)</th>
<th>p value</th>
<th>Speed × Pres. dur. F(1,31)</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking error</td>
<td>&lt; 0.01</td>
<td>0.96</td>
<td>1771.33</td>
<td>&lt; 0.001</td>
<td>42.75</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Velocity gain</td>
<td>453.84</td>
<td>&lt; 0.001</td>
<td>863.21</td>
<td>&lt; 0.001</td>
<td>7.26</td>
<td>0.007</td>
</tr>
<tr>
<td>Peak velocity</td>
<td>32.59</td>
<td>&lt; 0.001</td>
<td>736.70</td>
<td>&lt; 0.001</td>
<td>57.76</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Cum. saccades</td>
<td>996.31</td>
<td>&lt; 0.001</td>
<td>342.02</td>
<td>&lt; 0.001</td>
<td>78.46</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

Similar to the finger interception error, the eye tracking error (average 2D error between target and eye position across the entire trial) shows a speed range effect (figure 3.2 A). The eye velocity gain (ratio of eye and target velocity) systematically increases with increasing presentation duration and decreases for faster target speeds (figure 3.2 B). The eye peak velocity increases with increasing presentation duration (figure 3.2 C). Interestingly, the eye peak velocity decreases with increasing speed for the presentation duration of 100 ms, while it scales positively for 200 and 300 ms presentation duration. The cumulative saccades (sum of all saccade amplitudes across each trial) increases for higher speeds and slightly decreases for longer presentation duration (figure 3.2 D).
**Figure 3.2**: Effect of target properties (presentation duration and speed) on eye attributes. For each attribute, i.e. tracking error (A), eye velocity gain (B), eye peak velocity (C), and cumulative saccades (D), the mean values across all players and trials are shown for the respective conditions.

### 3.2 Attribute Selection

Experimentally a large set of eye movement and finger movement attributes were analyzed and computed. These measures were reduced to a smaller, non-redundant set of 14 target, eye, and finger attributes (see Table 3.3). The target attributes were: speed, presentation duration and feedback position or memory. The
true position of the target was shown to the player (feedback) at the end of each trial, that is, after he intercepted at the estimated position (figure 2.4D). The visual feedback positions shown in all previous trials were averaged for each of the three respective target speeds. This averaged position was then compared to the interception position of the current trial, yielding a measure of feedback information, or memory, players used to intercept.

Table 3.3: Target, eye, and finger attributes for eye-hand coordination task. Highly correlated measures were reduced to fewer attributes.

<table>
<thead>
<tr>
<th>Target</th>
<th>Eye measures</th>
<th>Finger</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed</td>
<td>Eye latency</td>
<td>Mean velocity</td>
</tr>
<tr>
<td>Presentation duration</td>
<td>Velocity gain</td>
<td>Peak velocity</td>
</tr>
<tr>
<td>Feedback (memory)</td>
<td>Total number</td>
<td>Mean acceleration</td>
</tr>
<tr>
<td></td>
<td>2D tracking error</td>
<td>Peak acceleration</td>
</tr>
<tr>
<td></td>
<td>Mean amplitude</td>
<td>Latency</td>
</tr>
<tr>
<td></td>
<td>2D velocity error</td>
<td>Movement time</td>
</tr>
<tr>
<td></td>
<td>Peak velocity</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tracking time</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Initial amplitude</td>
<td></td>
</tr>
<tr>
<td>Speed</td>
<td>Cumulative amplitude</td>
<td>Peak velocity</td>
</tr>
<tr>
<td>Presentation duration</td>
<td>Initial amplitude</td>
<td>Latency</td>
</tr>
<tr>
<td>Feedback (memory)</td>
<td>Movement time</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Quick eye movements, that is saccades, and pursuit eye movements were analyzed separately. As pursuit initiation and open loop parameter, eye latency and peak velocity were chosen. Open loop mean velocity as well as mean and peak acceleration were highly correlated with the peak velocity and were thus not included in further modeling. Similarly, the tracking error, that is, the 2D error between target and eye position across the entire trial, was correlated to the 2D velocity error. Consequently, velocity gain (ratio of eye velocity and target speed), peak pursuit velocity, and tracking error were chosen as closed loop attributes. Additionally, the smooth tracking time for which smooth pursuit was maintained after target disappearance (i.e. until initial saccade onset), held as a pursuit quality measure. As discussed in chapter 1.1.1 there is a consistent relationship between saccade amplitude and saccadic peak velocity or mean duration, respectively. Thus, saccadic measures were reduced to cumulative saccadic eye movements (total number of saccades times the mean amplitude) as well as the size of the initial saccade made.
in each trial. Finger measures were reduced to the peak velocity, hand movement latency, as well as the time it took from hand motion onset to interception (movement time).

![Boxplots of prediction attributes (9 test runs) sorted based on their importance score during random forest regression. The single most important attribute is the tracking error, indicated in red.](image)

**Figure 3.3:** Boxplots of prediction attributes (9 test runs) sorted based on their importance score during random forest regression. The single most important attribute is the tracking error, indicated in red.

Next, the set of chosen attributes was analyzed with the Boruta R package (see section 2.3.1). All attributes were ranked according to their relevance when predicting the output variable using a random forest algorithm. 9 importance source runs were performed (confidence level of 95%). Importance was scored between 0 (not relevant) and 1 (most relevant) for each run. Subsequently, the averaged importance score of each attribute across all runs was compared to the averaged importance score of a random shadow variable. All variables were found to be significantly more important for predicting the output ($p < 0.05$) than the random shadow attribute (importance score of 0.02 ± 0.006). Using the random forest algorithm, the most important predictor attribute is found to be the tracking error,
followed by feedback position (memory), and target speed (compare figure 3.3). Accordingly, the tracking error was used as a predictor for regression models with a single predictor and the entire subset of 14 predictor attributes was used for statistical models with multiple predictors.

3.3 Finger Interception Accuracy

This section focuses on the dependent measure, that is, the 2D finger interception error. First, pursuit quality is related to the quality of the manual interception. Next, the temporal evolution of the relationship between tracking and interception accuracy during the time course of a trial is investigated more closely. Then, the role of feedback (memory) is explored. Lastly, the interception accuracy is broken down into a temporal and a spatial component as shown in figure 3.9.

3.3.1 Manual Interception and Pursuit Quality

Interception accuracy improves with more accurate smooth pursuit eye movements, that is, smaller tracking error (figure 3.4) and fewer saccades of smaller size (figure 3.5). The averaged 2D tracking error of every player is related to the finger interception error, separated for the three different presentation durations (figure 3.4 panel A to C) and speeds. In each panel the three different speeds are indicated by color (24.1°/s: blue; 29.3°/s: green; 34.2°/s: red). A linear regression is fitted

![Figure 3.4](image_url)

**Figure 3.4:** Relationship between tracking and interception error averaged across every player and condition. Relationships are plotted for the respective presentation durations in panel A-C. Different target speeds are coded in blue (24.1°/s), green (29.3°/s), and red (34.2°/s). The quality of the linear regression fits are summarized in each panel.

36
for each respective condition. The relationship is strongest for the fastest speed and a presentation duration of 200 ms (figure 3.4 B). The linear regressions show a significant relationship between tracking and interception error for both, medium and fast speed levels, for all three presentation durations. However, the relationship between the eye tracking and the finger interception error is very poor for the slowest speed ($R^2 < 0.2$ for each respective presentation duration).

Likewise, figure 3.5 relates the cumulative saccades to the finger interception error. Generally, more saccadic eye movements yield a higher interception error.

![Figure 3.5: Relationship between cumulative saccades and interception error averaged across every player and condition. Relationships are plotted for the respective presentation durations in panel A-C. Different target speeds are coded in blue (24.1°/s), green (29.3°/s), and red (34.2°/s). The quality of the linear regression fits are summarized in each panel.]

These results are comparable with the results of the tracking error: The relationship is strongest for the highest speed and 200 ms presentation duration (figure 3.5 B). Again, the linear model shows a significant relationship between eye movements and finger interception accuracy for the medium (29.3°/s) and high (34.2°/s) speed levels, while the relationship is poor for the slowest speed ($R^2 \leq 0.1$ for each respective presentation duration).

Accordingly, results for the two higher target speeds are consistent: A smoother tracking supports a more accurate interception (lower error). For the slowest speed, however, the relationship is not as clear. To investigate this further, the eye velocity gain is plotted for the slowest target speed only in figure 3.6. Here, a higher gain denotes smoother eye movements, that is, the eye’s velocity follows the target
speed more accurately, the closer the gain is to 1. The linear regression model between velocity gain and interception error is significant for the slowest target speed ($F(1,94)= 16.63, \ p < 0.001$). Thus, better pursuit eye movements, that is, closer tracking of the target, yield more accurate manual interceptions.

![Figure 3.6: Mean velocity gain values for each player, averaged over for the slowest speed and every presentation duration (indicated by symbols). With higher gain, the interception error decreases.](image)

### 3.3.2 Temporal Evolution of Tracking Towards Interception

The temporal evolution of the relationship between the tracking and interception error for a presentation duration of 200 ms is shown in figure 3.7. Trials are aligned at the point of interception and then segmented into 150 ms intervals going backwards in time. Same results were found for 100 and 300 ms presentation duration (not shown). The plot shows that over the time course of each trial (from A to D) the relationship between the tracking and interception accuracy increases. Shortly before the time of interception the relationship is strongest ($R^2 \geq 0.47$ for all three speeds) and the variability between players is smallest (compare figure 3.7)
Figure 3.7: Temporal evolution of relationship between tracking error and interception error for a presentation duration of 200 ms. Different target speeds are coded in blue (24.1°/s), green (29.3°/s), and red (34.2°/s). Trials are aligned at the point of interception (D) and then segmented into equal time intervals of 150 ms going backwards in time (D-A).

D). In the early phase of the trial, the relationship is not clear, especially for the slowest target speed. Here, the tracking error is still comparably low for a majority of all players, which does not necessarily relate to how accurate the interception was at the end of the trial (figure 3.7 A-B). For these time interval the tracking error of the slowest target has no significant effect on the interception error ($p > 0.5$).
3.3.3 The Role of Feedback or Memory

As discussed in section 3.2, the role of visual feedback at the end of each trial was considered in the form of a feedback, or memory, attribute. Hereby, the manual interception position of each trial was compared to the average feedback position of the respective target speed shown in all previous trials. Thus, the smaller the value of the memory attribute, the closer the manual interception to the previously shown visual feedback. Figure 3.8 shows how this feedback (memory) attribute relates to the interception error. For the medium speed there is a very strong relationship: The closer the player intercepted to the visually shown feedback, the more accurate the interception. This relationship is similar but weaker for the fastest speed. For the shortest presentation duration of 100 ms (figure 3.8 A) the linear model does not reach significance ($p > 0.1$), while for the longer presentation durations (figure 3.8 B and C) the memory attribute has a significant effect on the interception error ($p < 0.05$).

Interestingly, the relationship is negative for the slowest target speed, that is, the interception error decreases with interception further away from the feedback position given. This is consistent across all three presentation durations and strongest for the 100 ms presentation duration ($R^2 = 0.22$). This could indicate that timing the interception was particularly difficult for the slowest target speed, since a low

**Figure 3.8:** Relationship between memory and interception error averaged across every player and condition. Relationships are plotted for the respective presentation durations in panel A-C. Different target speeds are coded in blue (24.1°/s), green (29.3°/s), and red (34.2°/s). The quality of the linear regression fits are summarized in each panel.
memory value only means that the interception was spatially close to the previously shown feedback.

### 3.3.4 Timing and Spatial Interception Error

The previous sections related the 2D interception error to different eye movement attributes. However, the interception might be performed at exactly the right time but spatially off the trajectory, or the interception might lie on the simulated trajectory path but is not timed correctly (figure 3.9). Thus, the interception error is separated into a spatial and a timing component.

![Diagram showing 2D interception error, timing error, and spatial error](image)

**Figure 3.9:** The main dependent measure is the 2D interception error (dark blue). The vertical distance to the simulated trajectory is the spatial error (purple). The distance along the trajectory describes the timing error (green).

Figure 3.10 shows the relation between the timing and the spatial error. As expected, player intercept too early, i.e. ahead of the actual target (positive timing error) for the slowest speed, and too late, i.e. behind the target (negative timing error) for the fastest target. Similarly, the spatial error is mainly positive (above trajectory) for the slowest speed, and negative (below the trajectory) for the fastest speed. These spatial errors are related to the different trajectory shapes for the
three different initial speeds (compare figure 2.3). Generally, the timing error is slightly larger than the spatial error (data points below identity). This is especially the case for the slowest target speed. As expected, both, timing and spatial errors are greatest for the shortest presentation duration (solid circles in figure 3.10).

**Figure 3.10:** Interception error broken down into a timing and spatial a component for the three different presentation durations (100 ms: circles, 200 ms: triangles, 300 ms: rectangles) and target speeds (24.1°/s: blue, 29.3°/s: green, 34.2°/s: red).

How much the target properties effect the timing and spatial component of the interception error becomes even more apparent when looking at the averaged values across all players per condition (figure 3.11). Both errors range widest for the shortest presentation duration. The timing error remains approximately the same for a target speed of 29.3°/s across all 3 presentation durations, while the spatial error slightly decreases to an underestimation (negative) for 300 ms presentation duration. Timing and spatial errors for the fastest target are largest for 100 ms pre-
sentation duration and approach zero for timing and slightly below zero (underestimation) for the spatial error. The slowest speed is most effected: Both spatial and timing error are highest compared to the other speeds for each condition. Spatially the error for a target speed of 24.1°/s approaches 0 (0.46 ± 0.21°) for a presentation duration of 300 ms, however, the timing error remains more than a degree (1.53 ± 0.25°) ahead of the actual target.

**Figure 3.11:** Effect of target properties (presentation duration and speed) on time and space component of interception error. Both measures are averaged across all players and trials and are shown for the respective conditions.

Similarly to section 3.2, the given target, eye, and finger attributes can be ranked by importance with respect to the timing or spatial component of the interception error. For both type of errors the target speed is the attribute of most importance (compare figure 3.12). Interestingly, for the timing error the finger latency is the attribute of second most importance (3.12 A), while for the spatial error the feedback, or memory, attribute ranks second (3.12 B). Eye attributes, that is, cumulative saccades and tracking error rank very similarly for both errors. Thus, finger attributes (latency and movement time) seem to be more important for timing the interception while the visual feedback given influences the spatial component of the interception.
Figure 3.12: Boxplots of most important prediction attributes sorted based on their importance score during random forest regression for the timing interception error (A) and the spatial interception error (B).

3.4 Statistical Models

In a first step a linear and a polynomial regression is fitted to the attribute of most importance (compare section 3.2). Then, the performance of three different statistical models fitted to the whole set of attributes is compared. Models are fitted to the training data set $D$ ($N = 7896$ observations) collected from the UBC 2013/2014 varsity baseball team and subsequently parsed as described in section 2.1. To test the fitted models, a test data set $\tilde{D}$ ($N = 2572$ observations) was used
consisting of collected data from 10 new players that joined the team after the original data collection.

### 3.4.1 Single Predictor Regression

As single predictor attribute, the tracking error was chosen in accordance with the previously run attribute selection (compare section 3.2). A linear, quadratic, and cubic regression was fitted to the training Data set $D$ and then tested on the test data set $\tilde{D}$. Table 3.4 summarizes the results. Here, the root mean square error (RMSE) is a measure of how accurate the model predicted the test data, the Pearson coefficient and the $R^2$ value indicate how well the model fits the data set and the p-value indicates if the tracking error has a significant effect on the interception error.

<table>
<thead>
<tr>
<th>Polynomial</th>
<th>RMSE $[\circ]$</th>
<th>Pearson c</th>
<th>$R^2$</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.510</td>
<td>0.460</td>
<td>0.236</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>2</td>
<td>1.507</td>
<td>0.467</td>
<td>0.244</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>3</td>
<td>1.507</td>
<td>0.467</td>
<td>0.244</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

The accuracy of the prediction does not increase significantly with a higher polynomial dimension. The coefficients of the cubic regression were fitted to

$$y_i = 2.42 + 67.89 x_i + 11.89 x_i^2 - 0.57 x_i^3.$$ (3.1)

The third coefficient in equation $3.1$, $\beta_3 = -0.57$ was the only coefficient that did not reach significance ($p > 0.5$). Thus, further polynomial regressions of higher degree were neglected and the quadratic regression was chosen to hold as a baseline reference for the following statistical modeling approaches.
3.4.2 Multiple Linear Regression Model

All attributes were fitted to the output variable (interception error) by means of multiple linear regression. Coefficients estimation and significance levels are summarized in table 3.5.

Table 3.5: Fitted coefficients for multiple linear regression. The p-values indicate the significance of different attributes.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Estimate</th>
<th>Standard error</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$ (intercept)</td>
<td>0.600</td>
<td>0.228</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Tracking error</td>
<td>0.889</td>
<td>0.023</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Feedback (memory)</td>
<td>0.080</td>
<td>0.010</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Target speed</td>
<td>-0.041</td>
<td>0.004</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Finger movement time</td>
<td>$-2.1 \cdot 10^{-4}$</td>
<td>$2.2 \cdot 10^{-4}$</td>
<td>0.35</td>
</tr>
<tr>
<td>Cumulative saccades</td>
<td>0.010</td>
<td>0.005</td>
<td>0.06</td>
</tr>
<tr>
<td>Finger latency</td>
<td>-0.001</td>
<td>$1.9 \cdot 10^{-4}$</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Finger peak velocity</td>
<td>3.624</td>
<td>2.262</td>
<td>0.11</td>
</tr>
<tr>
<td>Eye peak velocity</td>
<td>0.007</td>
<td>0.002</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Target presentation duration</td>
<td>$-2.8 \cdot 10^{-4}$</td>
<td>$2.6 \cdot 10^{-4}$</td>
<td>0.28</td>
</tr>
<tr>
<td>Initial saccade amplitude</td>
<td>-0.043</td>
<td>0.007</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Eye velocity gain</td>
<td>-0.127</td>
<td>0.068</td>
<td>0.06</td>
</tr>
<tr>
<td>Eye latency</td>
<td>-0.002</td>
<td>$2.5 \cdot 10^{-4}$</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Open loop peak velocity</td>
<td>0.005</td>
<td>0.002</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Tracking time</td>
<td>$1 \cdot 10^{-3}$</td>
<td>$2.6 \cdot 10^{-4}$</td>
<td>&lt; 0.01</td>
</tr>
</tbody>
</table>

Target presentation duration, finger movement time, and finger peak velocity were the only attributes that did not reach significance (p-value > 0.1) for the multiple linear regression model. The error between model predictions and actual test values came to RMSE = 1.488°, the Pearson coefficient was $r = 0.488$ and the model fit $R^2 = 0.268$. The model accuracy was consequently improved compared to the single attribute prediction (compare table 3.8). Removing the non-significant
variables from the data set did not improve the model accuracy (RMSE = 1.493 °, c = 0.482, $R^2 = 0.264$).

### 3.4.3 Regression Model Tree

Regression model trees were built using the Cubist R package. Figure 3.13 shows the result for a regression tree built without boosting. The model consists of 23 rules, that is, 23 different linear regressions have been fitted at all terminal leaves. Predictions are made following the decision rules at each split. This model improved the prediction accuracy compared to the multiple linear regression by 0.1 °, or $\approx 7\%$ (RMSE $= 1.390 °$, c $= 0.582$).

Figure 3.13: Regression model tree without boosting. Linear regressions (LR) have been fitted at the terminal leaves resulting in 23 rules.

To improve the model performance, the regression tree was boosted, that is, after building the original tree, several subsequent trees were grown, each one learning from the model fits of the previous tree. To improve prediction accuracy an instance based correction was added. Hereby, predictions are adjusted by taking nearby instances in the training set into account. Figure 3.14 shows how the
model accuracy improves for different number of training instances and committees. The model accuracy improves with increasing number of boosting iterations (committees). The model prediction performs poorest for 1 instance and best for 9 instances. Accordingly, 100 committees and 9 instances were chosen for the Cubist R model tree. With these parameters the model accuracy was increased to $\text{RMSE} = 1.304^\circ$ and the correlation to $c = 0.639$.

![Figure 3.14: Evaluation of boosting and prediction adjustment parameters. With increasing number of committees the prediction error decreases. An instance based correction with 9 instances yields the best model fit.](image)

Table 3.6 summarizes the attribute usage of all linear models at the terminal leaves. The sign in the third column indicates how the predicted interception error depends on the different attributes. The $\oplus$ sign indicates an increasing interception error with increasing attribute values, while $\ominus$ indicates an increasing interception error with decreasing attribute values. Finger latency and movement time show a mixed effect: For very high finger latencies and movement times the dependency...
switches and an increasing movement time yields a higher interception error. The indicated feedback position generally shows a positive relationship to the interception error, that is, an interception further away from the learned feedback position yields a higher interception error. However, for the slowest target speed, the relationship changes. This could be due to a greater timing error for the slowest target speed. For saccadic eye movements, the interception error increases with more saccades of higher amplitude. For trials in which the tracking error is very high (> 3.1 °), correctional saccades of higher amplitude decrease the interception error.

Table 3.6: Attribute usage of regression models at terminal leaves of the Cubist R tree with 100 committees and a prediction adjustment of 9 instances. The interception error either increases with increasing (⊕) or decreasing (⊖) attribute values. 4 variables show mixed effects.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Usage</th>
<th>Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking error</td>
<td>86%</td>
<td>⊕</td>
</tr>
<tr>
<td>Finger latency</td>
<td>84%</td>
<td>⊖ (⊕)</td>
</tr>
<tr>
<td>Finger movement time</td>
<td>80%</td>
<td>⊖ (⊕)</td>
</tr>
<tr>
<td>Feedback (memory)</td>
<td>74%</td>
<td>⊕ (⊖)</td>
</tr>
<tr>
<td>Cumulative saccades</td>
<td>72%</td>
<td>⊕ (⊖)</td>
</tr>
<tr>
<td>Target speed</td>
<td>71%</td>
<td>⊖</td>
</tr>
<tr>
<td>Initial saccade amplitude</td>
<td>62%</td>
<td>⊖</td>
</tr>
<tr>
<td>Eye latency</td>
<td>56%</td>
<td>⊕</td>
</tr>
<tr>
<td>Tracking time</td>
<td>51%</td>
<td>⊕</td>
</tr>
<tr>
<td>Target presentation duration</td>
<td>38%</td>
<td>⊖</td>
</tr>
<tr>
<td>Finger peak velocity</td>
<td>37%</td>
<td>⊖</td>
</tr>
<tr>
<td>Eye peak velocity</td>
<td>36%</td>
<td>⊕</td>
</tr>
<tr>
<td>Velocity gain</td>
<td>15%</td>
<td>⊖</td>
</tr>
<tr>
<td>Open loop peak velocity</td>
<td>8%</td>
<td>⊕</td>
</tr>
</tbody>
</table>

3.4.4 Neural Network

The brnn R package software minimizes the objective function $F = \beta E_D + \alpha E_W$, with $E_D$ denoting the error sum of squares of the actual output values com-
pared to the predicted values in the training set, and $E_W$ the sum of squares of the networks weights and biases (see section 2.3.6 for more details). Table 3.7 compares the model performance and parameters for different numbers of hidden layer units (neurons). The neural network with the same number of neurons (14) as attributes listed in table 3.3 has the lowest RMSE ($1.271^\circ$) and was thus chosen for further analysis.

**Table 3.7:** Feed-forward neural network using Bayesian regularization. Results for different number of hidden units (neurons).

<table>
<thead>
<tr>
<th># Neurons</th>
<th>RMSE [°]</th>
<th>Pearson c</th>
<th>$\alpha$</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.480</td>
<td>0.499</td>
<td>3.995</td>
<td>34.28</td>
</tr>
<tr>
<td>6</td>
<td>1.304</td>
<td>0.655</td>
<td>0.864</td>
<td>54.20</td>
</tr>
<tr>
<td>14</td>
<td>1.271</td>
<td>0.674</td>
<td>0.832</td>
<td>61.34</td>
</tr>
<tr>
<td>20</td>
<td>1.348</td>
<td>0.636</td>
<td>1.034</td>
<td>64.19</td>
</tr>
</tbody>
</table>

The structure of the neural net is shown in figure 3.15. On the left hand side 14 input attributes feed into the hidden layer, containing 14 neurons. Additionally, a bias term is added to each hidden input unit. While black lines indicate positive (+) weights, grey lines indicate negative (-) weights. The magnitude of the weights is coded by the thickness of the line. 7 attributes have ‘thick’ connections to the hidden units. Target speed and feedback (memory) have negative weights to neuron 9. Eye velocity gain, cumulative saccades, and finger latency have positive weights to neuron 14. The tracking error has positive weights to neuron 7 (which is also strongly biased) and neuron 11. The cumulative saccades attribute has a strong negative connection to neuron 13. Finally, finger latency and movement time have positive weights to neuron 13. Neurons 1 and 14 have a strong positive weight to the output, while neurons 7 and 13 have a negative weight to the output unit. This relationship, however, is not linear.
Figure 3.15: Feed-forward neural network using Bayesian regularization for 14 input attributes I1—I14 and 14 hidden units (neurons) H1—H14. The weights are color-coded by sign (black +, grey -) and the magnitude of the connections is coded by thickness. A bias term feeds into each neuron. The output O1 is connected to every neuron via a single weight. Input attributes indicated in bold are the attributes with the connections of highest magnitude.
3.4.5 Model Comparison

Table 3.8 summarizes and compares the different statistical training models applied to the data set $D$. The neural net performs best in predicting the output variable on a separate training set $\tilde{D}$, followed by the model tree.

Table 3.8: Evaluation of different statistical models applied.

<table>
<thead>
<tr>
<th>Statistical model</th>
<th># Predictors</th>
<th>RMSE [°]</th>
<th>Pearson c</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quadratic regression</td>
<td>1</td>
<td>1.507</td>
<td>0.467</td>
</tr>
<tr>
<td>Multiple linear regression</td>
<td>14</td>
<td>1.488</td>
<td>0.488</td>
</tr>
<tr>
<td>Cubist model tree</td>
<td>14</td>
<td>1.304</td>
<td>0.639</td>
</tr>
<tr>
<td>brnn Neural net</td>
<td>14</td>
<td>1.271</td>
<td>0.674</td>
</tr>
</tbody>
</table>

3.5 Interception Strategy

All data were analyzed with respect to individual player performance. Different aspects, such as player's position, years spent on the team, visual acuity, or contrast sensitivity were related to the interception performance. Additionally, interception accuracy was compared in between blocks and hands. Although, this analysis showed a few interesting trends, no clear conclusions have been drawn so far. Discussing these observational results in detail are beyond the scope of this thesis and will thus not be reported further.

In the eye-hand coordination task, a positive relationship between the time of invisible flight (time from stimulus disappearance to point of interception) and the interception error was generally observed (figure 3.16). The linear regression model between these two measures is significant ($F(1,94), p < 0.0001$). Thus, the strategy to intercept the ball as soon as it enters the designated hit zone may be beneficial for this particular eye-hand coordination task. Based on this observation the question arises whether players use different strategies when to intercept.
Figure 3.16: Relationship between the time of invisible flight (from time of disappearance to time of interception) and finger interception error. Data shown are for all presentation durations, while the target speed is coded by color (24.1°/s: blue, 29.3°/s: green, 34.2°/s: red).

As described in section 2.3.2 the favored time of interception was determined for each player by means of a Hazard analysis. Based on these peak values, all players were separated into two groups of early and late interceptors (figure 3.17 A). The division was done by a k-means clustering analysis with two clusters (early and late), while the hazard peak levels represented the dependent variable. The cluster centers were at peak interception times of 725 ms (early) and 940 ms (late) after stimulus disappearance. The averaged hazard level for both respective groups is plotted in figure 3.17 B. The earliest interceptions were made approximately 275 ms after disappearance. The ball was invisible for at least 250 ms (fastest speed and longest presentation duration) before it entered the designated hit zone. The Hazard curve of the early interceptors has a sharp peak at 750 ms, while the broader Hazard curve of the late interceptors peaks approximately 200 ms later.
Figure 3.17: Hazard level analysis. All players are divided into a group of early interceptors ($N = 17$) and late interceptors ($N = 15$) based on a k-means clustering analysis (A). Within each group the hazard levels are averaged (B).

The eye and finger attributes of these two groups can now be analyzed using one of the statistical models described in section 3.4. In particular, the Cubist R model tree was run on the data sets of both groups separately. Table 3.9 summarizes the results. The tracking error scales positive with the finger interception error and is still the attribute used most for predicting the interception error for both groups. For early interceptors the feedback component is the attribute that the model uses second most. It mostly scales positively with the finger interception error (inter-
Table 3.9: Cubist model tree results compared between early and late interceptors. The interception error either increases with increasing (⊕) or decreasing (⊖) attribute values. Some variables show mixed effects.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Usage</th>
<th>Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking error</td>
<td>87%</td>
<td>⊕</td>
</tr>
<tr>
<td>Initial sac. amplitude</td>
<td>63%</td>
<td>⊕</td>
</tr>
<tr>
<td>Target speed</td>
<td>59%</td>
<td>⊕</td>
</tr>
<tr>
<td>Eye latency</td>
<td>57%</td>
<td>⊕</td>
</tr>
<tr>
<td>Eye peak velocity</td>
<td>53%</td>
<td>⊕</td>
</tr>
<tr>
<td>Feedback (memory)</td>
<td>52%</td>
<td>⊕</td>
</tr>
<tr>
<td>Tracking time</td>
<td>49%</td>
<td>⊕</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Usage</th>
<th>Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking error</td>
<td>88%</td>
<td>⊕</td>
</tr>
<tr>
<td>Feedback (memory)</td>
<td>85%</td>
<td>⊕ ⊕</td>
</tr>
<tr>
<td>Finger latency</td>
<td>83%</td>
<td>⊕ ⊕</td>
</tr>
<tr>
<td>Target speed</td>
<td>80%</td>
<td>⊕ ⊕</td>
</tr>
<tr>
<td>Finger move time</td>
<td>78%</td>
<td>⊕ ⊕</td>
</tr>
<tr>
<td>Eye latency</td>
<td>67%</td>
<td>⊕</td>
</tr>
<tr>
<td>Cumulative saccades</td>
<td>60%</td>
<td>⊕</td>
</tr>
</tbody>
</table>

Exceptions further away from the feedback position yields a higher interception error) except for the slowest target speed, where the relationship is inverted. Third, the finger latency is important for the model prediction of early interceptors. For the latency the relationship with the interception error is mixed, that is, for very short latencies the relationship is negative, while for latencies higher than 450 ms the relationship is positive. For both early and late interceptors the relationship of the target speed is mixed, which is a consequence of the speed range effect discussed earlier. Generally, the target speed is mainly used for defining the tree’s splitting rules and is only part of some of the linear regressions models at the terminal leafs. For late interceptors, a larger initial saccade amplitude leads to a higher finger interception error and is the attribute, which the model uses second most. This positive relationship is in contrast to the results of the model on the entire data set (compare table 3.6), where the a larger initial saccade predicted smaller interception error. Interestingly, eye latency scales negatively for late interceptors, that is, a later eye movement onset is beneficial for late interceptors. However, both groups pursuit on average anticipatory. Thus, a later eye movement onset brings the eye movement closer to the actual target onset. As opposed to the early interceptors, the memory component of the late interceptors scales negatively for the highest target.
speed (not the slowest) and otherwise positively. Lastly, the tracking time scales positively. This could indicate that the eye lags behind for longer tracking periods resulting in larger catch up saccades.

Another interesting comparison between the two groups is to look at the eye velocity (figure 3.18 A), initial finger displacement (figure 3.18 B), and finger ve-

**Figure 3.18:** Early interceptors ($N = 17$) are plotted in dark blue and late interceptors ($N = 15$) in light blue. Averaged eye velocity (A) of each group across trials of medium speed ($29.3°/s$) and longest presentation duration (300 ms). True target velocity is indicated by the dashed grey line. Group comparison of initial finger displacement (B) and mean finger velocity (B).
locity (figure 3.18 C) averaged across early \((N = 17)\) and late interceptors \((N = 15)\) for a single exemplary condition (target speed of 29.3°/s, 100 ms presentation duration), respectively. While the eye velocity of the late interceptors is on average greater, the finger velocity is higher for the early interceptors. The initial finger displacement of the early interceptors follows a more direct path towards the screen, while late interceptors move earlier to the side and arrive at the scene further outside and at a later point of time.

Lastly, the different types of finger interception error were evaluated for both groups. Figure 3.19 plots the mean interception values for each condition and the two respective groups. The relative timing component of the interception error is plotted on the x-axis, while the spatial component is plotted on the y-axis. Overall timing errors were larger than spatial errors for both groups. Early interceptors (dark blue filling) performed better for the fastest speed (red bordered symbols), however poorer for the slowest target speed (blue bordered symbols). Early interceptors (cyan filling) had on average a smaller timing error compared to the early interceptors.

Figure 3.19: Average interception errors of early (dark blue filling) and late (cyan filling) interceptors broken down into relative timing (x) and spatial (y) component. Average for each presentation duration (symbols) and target speed (colors) as previously coded. Standard error of the mean error bars are included but to small to be visible.
In conclusion, both groups intercept best for the medium target speed. Early interceptors perform better for the fastest speed and their interception error increases consistently for a longer presentation duration. Late interceptors outperform the early group for the slow target speed and their timing remains better for almost all conditions.
4 Discussion

In this section, experimental results will be discussed and future research possibilities will be outlined. Section 4.1 will debate the effects of eye movements on the accuracy on manual interceptions. Then, the advantages and limitations of the statistical models applied will be discussed in section 4.3. Next, section 4.2 will focus on different interception strategies. Furthermore, practical implications will be presented in section 4.4 before a final conclusion is drawn in section 4.5.

4.1 Manual Interception Improves With Pursuit Quality

Overall, an improvement in interception accuracy is found for higher quality pursuit eye movements. This is in line with what we expected from the literature, where it has been shown that tracking a moving object with smooth pursuit eye movements enhances the observer’s ability to predict the target’s trajectory in time (Bennett et al., 2010) and space (Spering & Montagnini, 2011). Furthermore, intercepting a moving object critically relies on motion prediction (e.g. Soechting & Flanders, 2008). Thus, our findings are consistent with these previous studies and relate the quality of both eye and hand movements in a novel interception task.

To increase the degree of difficulty and to avoid memorization of a certain entrance points of the target into the hit zone, the target speed and presentation duration was varied randomly. These target properties significantly effected the interception error. Interestingly, the slowest target speed yielded, on average, the highest interception errors. The relationship between tracking error or cumulative saccades, respectively, and finger interception error was weakest for the slowest target speed. Moreover, relating the memory of the visual feedback positions to the finger interception error showed a negative relationship for this speed, that is, the
interception error was greater for trials that were intercepted closer to the feedback position. One possible explanation could be the fact that the memory attribute purely refers to the distance between the feedback position indicated in previous trials and does not take the timing of the interception into account. In line with this, the relationship between memory and the interception error is strongest for the medium speed. However, if this was the only effect, the relationship should be similar for the slowest and the highest speed, respectively, since we are comparing the memory feedback position to the 2D interception error (not the timing error).

Figure 2.3 illustrates another possible reason for the discrepancy: The apex of the simulated fly ball at this speed is reached before the target actually enters the hit zone. Since the target disappears before the apex is actually reached, it becomes very difficult to extrapolate the directional change of the trajectory for the slowest target speed. Mrotek & Soechting (2007a) showed that the direction of smooth pursuit follows the predicted direction of the target when the trajectory is occluded. In accordance with this, players might have predicted that the target continued rising until it entered the hit zone as is true for the fastest and medium target speed.

Manual interception as well as 2D eye tracking error both show a speed range effect (Poulton, 1975), which is the mean tracking and interception errors are lowest for the averaged (medium) speed. This is to be expected for three target speeds and could be avoided by, for example, changing the initial launch angles instead of the target speed. This way, variability in trajectory shape would still be ensured, while speed effects would be minimized. Furthermore, for the shortest presentation duration of 100 ms, the eye movement and manual interception quality is very poor. When the target is only visible for 100 ms, the smooth pursuit system is still in the open loop phase and hence the target has disappeared before visual feedback closes the loop to correct for eye positional error. Thus, this presentation duration might be too short to yield an accurate motion prediction and effects are consequently not as strong.

The separation into timing and spatial error yielded interesting results. The spatial error strongly depends on the memory of visual feedback given in all previous trials. In a study addressing movement planning, Brouwer & Knill (2009) found that their subjects integrated remembered target position from previous feedback given and peripheral visual information. In accordance with this, the spatial
position of the interception might be influenced by a movement plan relying on the feedback given in previous trials. Moreover, the timing of the interception depends more on movement initiation (finger latency) and is then guided by eye movement measures and feedback position. In general, timing the interception seemed to be slightly more challenging than hitting the trajectory path spatially (compare figure 3.10). This could be due to the previously discussed speed range effect, leading to early interceptions for slow and late interceptions for fast targets, respectively.

Finally, it should be noted that the separation into spatial and timing error was done by approximating the vertical distance to the simulated trajectory (spatial error) and then measuring the length of the spatial trajectory-intersection point to the true target feedback point (timing error). Instead, the spatial component could, for example, be chosen as the shortest distance to the simulated trajectory, or the timing error could be calculated based on the time that would have passed until the trajectory had reached the spatial trajectory-intersection point. These measures could be explored and compared in future analysis.

4.2 Interception Strategy

In general, it was shown that early interceptions were on average more accurate (compare figure 3.16). By intercepting the invisible ball as soon as it enters the hit zone, the player spatially minimizes horizontal error. It now becomes a task to estimate when the ball will reach the hit zone and where along a vertical line it will enter. Early interceptors, that might have followed this strategy, made comparably higher errors for the slowest target speed. Again, comparing figure 2.3, we see that the entrance points of the three trajectories are not evenly spaced, but the slowest speed enters at a much lower vertical position. Consequently, even though this strategy overall lead to a lower interception error in this task, it might not mean that early interceptors predicted the target motion more accurately over time. That is, even though late interceptions are more difficult in terms of spatial uncertainty, they might be more closely related to a baseball player’s performance out on the field. Here, a batter can not swing as soon as the ball crosses a certain point but has to time the bat perfectly. Figure 3.18 shows that the late interception group on average reaches a higher eye velocity, indicating that they might track the ball better.
and take longer to prepare their interception, relying more on their eye movements than on a remembered feedback position.

To explore this further, a future approach could be to change the task slightly: Instead of having a large hit zone on one side of the screen, where the ball enters horizontally, a smaller strike zone could be implemented. In particular, the ball would again disappear some time after launch off and then would have to be ‘caught’ (intercepted) once it vertically enters a smaller box. Additionally, catch trials, in which the ball misses the strike zone and the player consequently should not intercept, could be introduced. This way, the task would even more rely on precise motion prediction and the demands of the visuomotor coordination would be closely related to an actual baseball bat.

4.3 Statistical Models

Three different statistical models were compared for multiple attribute predictions. The multiple linear regression is easiest in terms of model computation and interpretation. Statistically, it provides information about attributes that have a significant effect on the dependent measure. Mathematically, the coefficients contain information about the relationship as well as strength between each attribute and the dependent measure. For example, a lower tracking error yields a lower interception error (positive relationship), while a higher eye velocity gain yields a lower interception error (negative relationship). A disadvantage of the multiple regression is that the fit is done across all samples, e.g. not taking into account different target properties. Accordingly, different target speeds or presentation duration might yield different attribute coefficients and relationships. Lastly, compared to the other statistical models applied, the multiple linear regression performs poorest for a prediction of the finger interception error on a training set (see table 3.8 for reference).

Conversely, the feedforward neural network predicts the interception error most accurately on a new test data set. However, the neural net structure is highly complex and the hidden layer works as a black box. The mapping from the hidden units to the output attribute is nonlinear and the weights are thus difficult to interpret. For interpretation of the functional significance of different input attributes this model
might thus not be optimal.

Finally, the regression model tree predicts the interception error of a test data set more accurately than the multiple regression analysis and is easier to interpret than the neural network. Here, the output of the model is a set of fixed rules resulting in several different linear regression models. The summary of the model yields an overview of attribute usage for building the splitting rules and the linear regressions, indicating the attribute importance with respect to the dependent measure. An advantage compared to the multiple linear regression is that linear models are fitted to smaller sub-samples of the entire data set, such as to the highest target speed only, or trials with very high tracking error. In conclusion, the regression model tree was best suited for exploratory analysis on e.g. attribute importance for different subject groups.

All of the models presented in this thesis make predictions based on averaged results across each trial. This way, the richness of the data set within one trial might be lost. For example, the tracking error across all trials could be extrapolated to be of same length. Next, these samples could be parsed by means of principal component analysis (PCA) or independent component analysis (ICA) to derive new attributes, that is the principal components. These components would also indicate at which time point the eye tracking error shows high variability between subjects. Another approach could be to consider a Bayesian framework for modelling the manual interception based on eye position data within each trial. In particular, a Kalman filter could be fitted to each eye position trace. It has already been shown in the literature that a Kalman filter can be used to model visually guided and predictive smooth pursuit eye movements (Orban de Xivry et al., 2013). This model could then be updated by the given feedback position at the end of each trial and be incorporated into a larger statistical model across all trials. Bayesian models have shown to be successful representations of e.g. multisensory information integration (Beierholm et al., 2008) or sensorimotor learning (Körding & Wolpert, 2004). This approach will be explored in future work.
4.4 Practical Implications

Vision training in sports is becoming a greater part of many professional programs every day (see Abernethy & Wood, 2001, for a review). Clark et al. (2012) reported that the batting average and slugging percentage of the Cincinnati university baseball team increased significantly between two seasons after systematically training the player’s vision. Similarly, Deveau et al. (2014) report that players of the University of California Riverside baseball team showed significant improvement in visual acuity and visual contrast sensitivity, as well as a lower number of strike outs and a higher number of runs created, after being part of a specific perceptual learning program. Many other studies and books report anecdotal evidence of improved athletic performance after vision or perceptual-cognitive training (e.g. Peters, 2012; Faubert & Sidebottom, 2012). However, these studies often lack a systematic scientific approach and do not consider for example placebo effects or matched control groups. Moreover, eye movements are often considered in terms of gaze strategies, that is fixational eye movements and not smooth pursuit. This study gives evidence that smooth tracking is beneficial for manual interceptions. Accordingly, these types of eye movements should be considered when designing a comprehensive and research based vision training.

The results of this study focused on averaged eye movement and interception behavior. This could also be broken down in individual player performance and strategy. This way strength and weaknesses of each player could be identified and individual consultation could be given to improve the performance of each player.

4.5 Conclusion

In the literature several studies have reported a strong connection between smooth pursuit eye movements and manual interception (e.g. Mrotek, 2013; Mrotek & Soechting, 2007b; Koken & Erkelens, 1992). This study shows that observers not only benefit from smooth pursuit eye movements in a manual interception task, but also that the interception accuracy scales with the quality of the eye movements. Additionally, two different interception strategies were identified. Earlier interceptions were biased towards a remembered visual feedback position and guided by fast hand movements as well as accurate tracking eye movements. Later intercep-
tions relied overall more of eye movement accuracy, that is low tracking error and initial saccade, precise eye latency and eye peak velocity.
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