ADAPTIVE CONTROL OF BULLDOZER’S WORKFLOWS

Alexey Bulgakov¹,⁴, Thomas Bock² and Georgy Tokmakov³
¹ South West State University, Russian Federation
² Technical University Munich, Germany
³ South Russian State Polytechnic University, Russian Federation
⁴ a.bulgakow@gmx.de

Abstract: The most important task for bulldozer’s traction mode control is to use its traction capacity in full by means of its end-effectors control. To keep traction mode at maximum or at a given resistance value applied to end-effectors automatically is difficult due to a great number of stochastic factors affecting the bulldozer. Bulldozer is taken as a mechatronic system [1, 2]. The study presents analytic dependences for the sub-processes where analytic modeling based on bulldozer’s parameters correlation knowledge is applicable. Models of the sub-processes are included into the general structure of bulldozer’s workflow simulation model. Simulation technique is demonstrated through model development of the bulldozer as a universal machine operating in modes of soil movement and subgrade surfacing. In developing the models mathematical apparatus of the theory of random processes, transfer functions, table interpolation, numerical solution of algebraic equations and ordinary differential equations in the Cauchy form was used. A dynamic model of the drawing prism formation was developed describing the dependence of the volume of prism on the variable digging depth and variable bulldozer speed. A general structure of the model of bulldozer’s workflows [3] due to the working process control objectives was developed.

1 INTRODUCTION

Bulldozers equipped with modern navigation and information systems are mobile mechatronic objects, and they can be integrated into general process of intellectual construction. The integration will provide optimal efficiency of the construction cycle and will ensure lean production process.

On the basis of bulldozer’s workflow dynamics modeling and analyses described in a variety of works, we have concluded that the models to describe kinematics and dynamics of its working equipment, hydraulic and transmission features tend to be analytical formulas derived from well-known laws of physics and from information on bulldozer’s structure and mechanisms. If some parameters of the workflow are unknown or constantly changing, the models are either statistical tables or empiric dependences summarizing experimental data. The models depict interaction of end-effectors, engines and environment as well as statistic features of bulldozer’s complex units.

Application of regulators based on classical control theory is difficult due to the frequent changes in workflow conditions. Thus, it is necessary to develop adapted control systems to eliminate the difficulties described. The system includes both the bulldozer’s dynamics modeling and bulldozer’s workflow control method to take into consideration the complex non-linear dependencies between workflow parameters and incomplete information on its working conditions changes.
Having reviewed adaptive and intellectual control methods [4, 5], we propose to create an adaptive control system for technological processes to increase efficiency of bulldozer’s control in comparison with traditional control methods.

2 MOBILE MECHATRONIC OBJECT - MATHEMATICAL DESCRIPTION TO PERFORM EXCAVATION WORKS ON THE BASIS OF A DOZER

When researching a dozer’s working process usually a number of design schemes are considered – straight line, thread milling, wedge and exponential cutting. Meanwhile, a dozer moves along the surface that is formed by its blade. Therefore, when driving onto any surface roughness resulting from the dozer blade control or the change in its position due to any reason, causes position changes of the machine frame and along with the cutting edge that is any face deviation from a straight line in some extent is copied by the dozer.

Observations [1] show that quite often while designing a face its roughness is progressing, reaching a size at which the control over the workflow is lost. In this case, the operator has to align the face deliberately, trying to ensure its “tranquil” profile that allows doing excavation works smoothly, without frequent control system switching and reducing the dozer’s operating speed that causes a slowdown and shows inferiorities of the blade control system. Obviously, if the control system operates in the antiphase towards deviations of the tractor frame with sufficient accuracy, the initial face roughness will not evolve and will be gradually cut. One of the most likely causes of the opposite phenomenon observed in practice, is the disparity between the velocity of the dozer \( V_p \) and actual conveying speed of the working body \( V_{\text{ot}} \) required in certain areas \( S_i \) of the digging operating cycle, where \( i \) is the number of the speed change \( V_{\text{ot}} \). Speed ratio depends on the dozer’s geometrical dimensions (Figure 1) and its control system.

Mathematical model of the dozer’s movement on a straight line tracking (frame alignment) is built using the Lagrange equations of the 2nd kind, under the assumption that the contribution to the dynamics of the drive gears and a track is small, compared with the contribution of the remaining parts of the dozer.

\[
\begin{align*}
\frac{d}{dt} \left( \frac{\partial T}{\partial \dot{x}} \right) - \frac{\partial T}{\partial x} &= Q_x \\
\frac{d}{dt} \left( \frac{\partial T}{\partial \dot{\varphi}} \right) - \frac{\partial T}{\partial \varphi} &= Q_\varphi
\end{align*}
\]

where kinetic energy:

\[ G = C_1C_2 + C_3C_4 + C_5 \]

Figure 1: Dozer’s geometrical dimensions
generalized forces acting on a dozer:

\[ Q_x = -\sigma gl_2 \sin \varphi + F_t - F_{comp}; \]

\[ Q_\varphi = -(m_2 l_{c2} + \sigma xh) gl_2 \cos \varphi + M; \]

\[ m_1 - \text{tractor mass; } m_2 - \text{blade frame mass; } \sigma - \text{soil surface density; } h - \text{depth of the soil cutting; } l_{c2} - \text{center of the blade mass; } i_{cz} - \text{gyration radius of the dumping soil.} \]

The system (1) solution allows getting the differential equations (4) and (5) that describe the dozer's movement on a straight line track, and determining control actions through the parameters of the machine in areas Si of the digging operating cycle as the coefficients a_i in the dependence \( V_{ot} = a_i V_p \).

Such a dependence is typical for dozers with a single-motor drive with a hard pump hydraulic drive connection to the motor shaft.

At the beginning of digging (Figure 2), the frame of the tractor makes a strictly forward movement over a distance of \( S_1 + S_2 \) without hesitation relatively its mass center. The blade cutting edge in the area \( S_1 \) dives into the soil to a depth equal to a predetermined cutting thickness \( h \). Thus, the control action \( a_1 \) may be determined by the formula:
\[ a_1 = \frac{30_1 m \cdot l_2 \cdot \pi \cdot n \cdot \rho \cdot C_0 \cdot n}{m_0 F_{2 \theta} \cdot n} \]

where \( i_{tr}, i_{pr} \) - tractor transmission and hydraulic pump ratios;
\( n \) - number of hydraulic cylinders;
\( m \) - fluid mass in the hydraulic cylinders;

In the area \( S_2 \) the movement is made with \( a_2 = 0 \) until the mass center of the tractor won't move to the buttonhole edge.

![Figure 3: Movement the dozer "dives" in the drawn buttonhole](image)

On further movement the dozer "dives" in the drawn buttonhole (Figure 3), so in the area \( S_3 \) it is necessary to lift the blade at a rate of \( V_{ot} \), determined by the coefficient \( a_3 \):

\[ a_3 = \tan \beta \left[ e^{\alpha V_{ot}} \left( 1 + \frac{aC_1}{C_1 + V_{ot}} \right) - 1 \right] \]

The area \( S_3 \) ends after the dozer's back gear hits the edge of the face and reverse alignment of tractor frame starts. Length of the alignment area is \( S_4 \approx S_1 \). Obviously, during this period it is necessary to start dropping the blade. The \( a_4 \) determines the rate of dropping the blade in the given area:

\[ a_4 = \frac{C_3 S_1}{(C_4 + S_3 + V_{ot})^2} \]

To implement control actions \( a_i = f(S_i, t, h) \) the dozer must be equipped with a vertical blade control system.

### 3 NEURAL NETWORK MODEL OF BULLDOZER WORKFLOW

The Autoregressive model structure with external inputs (Figure 4) is a dynamic two-layer recurrent neural network. It is found from the autocorrelation signal functions that the autocorrelation coefficient is greater than 0.8 in the time interval 0.1 sec. for speed \( v(t) \) of 0.5 sec. for digging depth \( h(t) \) and 0.2 sec for the resistance force \( P(t) \). Length of delay lines TDL taking into account the sampling frequency of 10 Hz are up to 1, 5 and 2 accordingly (Figure 4).
Figure 4: Neural network model for bulldozer’s bogie workflow.

Vector for adaptive model adjustable parameters comprising weights and displacements of neural network,

\[ [10] \mathbf{X} = [\mathbf{b}^1; \mathbf{b}^2; \mathbf{IW}^{1,1}; \mathbf{IW}^{1,2}; \mathbf{LW}^{1,2}; \mathbf{LW}^{2,1}] \]

Criterion for neural network model optimal tuning, i.e. current learning error at a given moment of time we take as follows:

\[ [11] F(\mathbf{X}) = e(t) = P(t) - a^2(t) \rightarrow 0 \]

The network learning task is the task of multiple non-linear optimization

\[ [12] \mathbf{X} = \arg \min_{\mathbf{X}} F \]

The author propose the bulldozer workflow neural network model adaptive learning algorithm based on the recurrent least square method (exponential forgetfulness method) and on the algorithm of Forward Perturbation or dynamic back propagation.

In the process of learning the neural network accumulates information on workflow dynamics, new tendencies of process development prevail on the earlier ones at that. Degree of importance for the previously learned information is considered with forgetfulness parameter \( \lambda \). Network optimal learning criterion gradient comprises frequent derived learning errors based on neural network model adjusted parameters:

\[ [13] \nabla F = \frac{\partial F}{\partial \mathbf{X}} = \left[ \frac{\partial F}{\partial \mathbf{b}^1}; \frac{\partial F}{\partial \mathbf{b}^2}; \frac{\partial F}{\partial \mathbf{IW}^{1,1}}; \frac{\partial F}{\partial \mathbf{IW}^{1,2}}; \frac{\partial F}{\partial \mathbf{LW}^{1,2}}; \frac{\partial F}{\partial \mathbf{LW}^{2,1}} \right] = -\nabla a^2 = \left[ -\frac{\partial a^2}{\partial \mathbf{b}^1}; -\frac{\partial a^2}{\partial \mathbf{b}^2}; -\frac{\partial a^2}{\partial \mathbf{IW}^{1,1}}; -\frac{\partial a^2}{\partial \mathbf{IW}^{1,2}}; -\frac{\partial a^2}{\partial \mathbf{LW}^{1,2}}; -\frac{\partial a^2}{\partial \mathbf{LW}^{2,1}} \right] \]

Software algorithm of adaptive learning for neural network model of bulldozer workflow has been designed and implemented. The weight vector and bias network \( \mathbf{X}(t) \) are adjusted in accordance with the recursive expressions at each time step:
Applying a hybrid neural network consisting of a combination of traditional neural networks and neural networks of higher order (Figure 5.). Thus, the neural network has the ability to switch between linear connections and connections of high order that can be described by the following dependencies.

**Linear coupling:**

\[ y_i = \sum (w_{ij} x_i + b_{j0}); \]

**High order coupling:**

\[ y_i = f \left( \prod x_i^{p_{ij}} * 1^{b_{j0}} \right); \]

**Activation function:**

\[ f(x) = \frac{1}{1 + e^{-ax}}; \]

where \( w_{ij} \) - coupling weight coefficients; \( y_i \) - output neuron signal; \( x_i \) - input neuron signal;

This implies that each layer depending on the operating mode, may change the type of connection between neurons. For example, for a neural network consisting of 3 layers, the following options are possible (linear - L, higher order - HO): L-L; L-HO; HO-L and HO-HO.

To optimize the created neural network is possible with the help of the genetic algorithm adaptation (Figure 6).
It is a method of random search with elements of adaptation, which is based on principles similar to the Darwin’s evolution process of biological organisms. In this case, three types of operations are performed: crossing, mutation, selection. The fitness degree (how the population corresponds to the given task) is defined through the fitness function that can also include penalty functions for violation of additional restrictions on variable variables. There are various forms of crossing [5]. They make a selection of the fittest specimen, which constitute a parental pair and the crisscrossing of the chromosomal chains takes place, i.e. the descendant line code inherits fragments of codes of parental chromosomes. The mutation operator produces a local change in the line code of chromosomes with a given probability, which is one of the configurable parameters of the genetic algorithm [5, 6].

The selection operator allows creating a new population from a set of specimen, generated and modified descendants of specimen after mutation. The genetic algorithm is used to adjust the membership functions that are defined within the accuracy of a few changeable parameters, such as triangular, trapezoidal, radial functions. When simultaneously configuring several membership functions, the parameters of each of them are coded by their own segment of the chromosome, so that during the process of crossing the code sharing occurs only between chromosome segments of the same type. To configure a rule base to a specific chromosome fragment, some variant of the rule base is corresponded and in accordance with the accepted coding the choice of the genetic operators’ type is performed. Thus, the architecture of the management and control system can be represented as follows (Figure 7).

To conduct researches on the basis of fuzzy modeling, quite versatile software have been developed [7] that greatly simplify the creation of new control systems using neural networks and fuzzy models. The use of different aspects of evolutionary modeling as a new direction of computing technology allows applying principles of learning for the management and control system and adaptation of the described hybrid neural network allows getting the following results.

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![Figure 6: Hybrid neural network optimization algorithm](image_url)
5 CONCLUSIONS AND RESULTS

Automatic control function of blade positions precisely adjusts the cutting edge. Depending on the content of correction signals, the regulating dual hydraulic valve automatically lifts or drops the cutting edge of the blade, constantly keeps it in position that ensures the accuracy of work and ensures an optimum level of productivity.

Identification technique of the dozer’s working processes and models obtained on its base, are intended to be used in the development of adaptive systems of automatic control of the dozer’s working process.

Methods of development of adaptive systems of control of the dozer’s working process, is based on neural network technology. For the formation of control actions on a dozer, and of the electrical switch signals of the hydraulic directional valves of the lifting and dropping hydraulic cylinders of the working body, in particular, the structure and functioning algorithms of the adaptive neural network controller have been designed.

References

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