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Modeling and simulation of vibrating ore drawing process based on visual perception and model predictive control

Introduction

The intelligent ore mining and transport process represents the current focal point of development within the metallurgical mining industry. Unmanned underground ore transport is an attractive emerging theme in the field of smart mining. For the chute release process, vibratory release technology has made a breakthrough (Liu et al. 2000). However,

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the Vibrating Ore Drawing Process (VODP), which loads the ore from the chute into railed mine cars, may still be primarily manual-based observation and operation. The low level of automation in the vibratory discharge machine, coupled with poor synergy with the ore car, inadequate ore detection, and insufficient operator competence bring great challenges to the automated ore loading operations, but the requirements of ensuring safe operations, reducing the production risks and improving the working conditions, especially the needs of achieving the green sustainable development, have called for artificial intelligence technology to meet those difficult tasks. Visual perception methods, e.g., YOLO, can provide information for low illumination, multiple glares, dust, and water mist, serving as an alternative for target recognition and parameter detection (Wei et al. 2024; Zheng et al. 2020). This motivated the first part of our study, concerning the detection of the parameters of the ore process by optimizing the resulting neural network, with the goal of modelling the dynamics of VODP. Note that general YOLO-based target detection performs poorly when dealing with small targets (Miao et al. 2020; Redmon et al. 2016), particularly those with a resolution of less than 32×32 pixels, due to their inadequate feature extraction capabilities. Compared with the traditional YOLO target detection algorithm (Zheng et al. 2020; Song et al. 2021), our proposed YOLOv5-MINE structure is optimized from the FPN-PAN fully connected structures, improving its feature extraction capability for small targets in harsh environments. Then, based on the parameters of the process, a reference model of VODP is constructed for the following controller design.

It can be observed that the specialized operating environment of equipment utilized in underground transport processes, coupled with the system's inherent uncertainty resulting from potential disturbances, presents unique challenges. Research on methods for controlling equipment in underground mining processes is scarce and ineffective in dealing with uncertainty. Model predictive control is one of the most effective control strategies, and that is, it is suitable as a control method for production equipment in underground mines (Qin et al. 2003; Zheng et al. 2014). This motivates the second part of our work, in which an MPC control strategy of ore draw is proposed to achieve the stable and controllable flow of the vibrating drawer at the chute outlet, such that the system model obtained through target detection is used to calculate the deviation from the actual vibratory discharge machine output, which continues to act as a feedback signal to the controller. The stability of the system gives a proof through Lyapunov's theorem.

The main objectives of this work are to study the following practical issues, which have been rarely addressed in the research domain:

1. A new YOLOv5-MINE neural network structure is developed to enhance the detection accuracy of small targets within underground mines. This optimized structure is employed to detect the ore loading volume of ore trucks specifically for VODP. Furthermore, an algorithm for calculating the ore flow rate has been proposed, paving the way for the establishment of a comprehensive input-output reference model tailored for ore flow rate management.
2. The effectiveness of MPC control in controlling the vibratory ore release process is verified, and the results are presented and analyzed in practical applications. It shows

that MPC is suitable for equipment control in underground mines, and can better interact with detection and communication equipment for information, and design a complete automated ore release operation process.

The article is organized as follows. The VODP description and problem formulation are presented in Section 1. Section 2 describes the optimization methodology for YOLOv5, and its optimized structure is established. Then, the construction of the system model is proposed through standard process monitoring. The MPC control method for VODP is presented in Section 4. The standard simulation case is given in Section 5, with the results of the application in the real production process. Concluding remarks are presented in the last chapter.

1. VODP description and problem formulation

1.1. VODP description

This article describes the real-time monitoring of the ore car's material level height using an industrial camera, establishing a relationship between the ore car's volume and the control parameters of the vibrating ore discharge machine to achieve fully automatic ore loading for the locomotive. After each ore car is loaded with ore, the system automatically assesses the loading status of the entire train based on the locomotive's position information and image recognition markers on the ore cars, determining whether to transport the loaded cars for unloading or to move to the next ore car for continued loading, as shown in Figure 1.
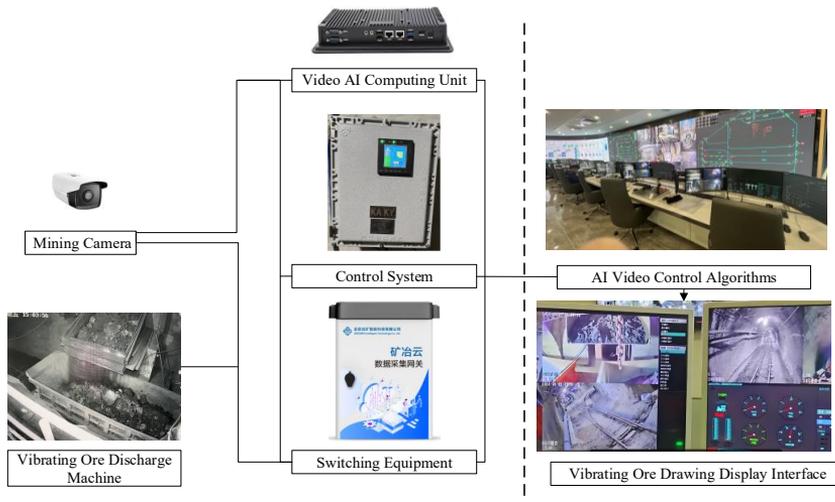

Fig. 1. Structural Diagram of the Automatic Ore Loading System

Rys. 1. Schemat strukturalny automatycznego systemu załadunku rudy

Fig. 2. Full load tramcar model and ore distribution

Rys. 2. Model tramwaju z pełnym obciążeniem i rozkład rudy

The basic principle of visual inspection is to extract the visible state features during the operation of the system and convert them into parameters. The detectable parameter in the ore drawing stage is the ore volume v in the mine car, which is an indirect measurement parameter that can be calculated according to the directly measured parameters of the loading depths h_1 and h_2 of the ore rock and the cross-sectional area S in the mine car. The parameters dynamically change during the whole process.

In the actual loading process, the falling process of ore and rock is affected by gravity factors, so it is not distributed in a standard horizontal state in the mine car, especially ore powder with a small particle size. According to empirical statistics, the distribution of ore rocks can be abstracted into a superimposed form of cones and cubes.

The upper and lower layers of ore are superimposed together, and the ideal loading volume v of the ore and rock loaded by the mine car can be expressed by the following Formula (1):

$$v = \left(\frac{1}{3} h_1 + h_2 \right) S \tag{1}$$

In this formula, h_1 and h_2 represent the depth of loaded rock in the mine car, and S is the cross-sectional area of the mine car. To determine the error e, assuming that the actual neural network detection volume is v_{cnn}, the error e between the estimated volume and the actual volume can be expressed as Formula (2):

$$\left| v_{cnn} - v \right| = e \tag{2}$$

Considering the size of ore and rock, the parameter δ of ore-rock lumpiness is introduced to optimize the estimated volume v. The ore lumpiness parameter δ represents the proportion of ore lumpiness. The smaller the value of δ is, the larger the proportion of ore with small lumpiness entering the mine car, and the actual detection volume is closer to the idealized model volume v. Among them v_{cnn}, is described by the block degree parameter as Formula (3):

$$v_{cnn} = \delta v \tag{3}$$

The constraint on δ is (4):

$$\delta < 1 \tag{4}$$

At this time, the volume error e can be calculated and expressed by Formula (5):

$$e = (1-\delta)v = (1-\delta)\left(\frac{1}{3}h_1 + h_2\right)S \tag{5}$$

The ore lumpiness is optimized, and the parameter v_{cnn} can be expressed by Formula (6):

$$v_{cnn} = \delta\left(\frac{1}{3}h_1 + h_2\right)S \tag{6}$$

The parameters δ, h_1, h_2, and S are directly measured by the visual sensor based on a neural network, which are the known state quantities of the minecart. v_{cnn} is calculated by the measured parameters and the above formula.

The rock flow parameter Q describes the volume of ore entering a single mine car per time at the mouth of the vibrating ore drawer. This parameter combines the time parameter t and the volume parameter v to dynamically describe the loading state of the mine car, which can be described by Formula (7):

$$Q = \frac{v_{cnn}}{t_1 - t_0} \tag{7}$$

The flow Q has units of cubic meters per second, the time when the vibrating ore drawing machine starts drawing ore is t_0, and t_1 describes when the predetermined ore loading amount is reached, and the ore-rock volume is v.

Through the on-site ore loading process, the ore volume required by each mine car from empty to full load and the ore drawing time t of the vibrating ore drawer are measured, and the average ore drawing flow Q_{eq} of the chute is calculated. The experimental data statistics are shown in Table 1. The parameter Q_{eq} represents the state parameter of a single mine car

Table 1.   Ore drawing flow calculation experiment

Tabela 1.   Eksperyment obliczania przepływu rudy

Trips	Body cross-sectional area (S/m²l)	Mining time (t/s)	Rock height (h/m)	Draw flow Q_{eq}
1	30	37	1.5	1.216
2	30	56	1.5	0.803
3	30	46	1.5	0.978
Average	30	46	1.5	0.978

reaching the full load state, but it cannot describe the change law of the flow parameter Q in the VODP process. A dynamic ore volume detection method needs to be introduced.

1.2. Problem formulation

In the context of unmanned driving for electric mining vehicles, the current process primarily relies on manual remote unloading from the surface, resulting in low efficiency and high labor intensity. Additionally, the existing methods for monitoring control parameters are not effective, and the applicability of Model Predictive Control (MPC) has yet to be validated in practical scenarios. There is a significant lack of real-world applications that demonstrate the effectiveness of MPC in the unloading phase of mining operations. This situation highlights the need for a more efficient, automated solution that can improve performance and reduce human labor in the unloading process.

Our objective is to implement a neural network-based detection system for monitoring parameters in the ore release process. However, the current effectiveness of neural network detection methods is limited when it comes to identifying small targets in underground mines. To address this challenge, we propose a novel architecture called YOLOv5-MINE, specifically designed for enhanced detection in mining environments.

In addition, while Model Predictive Control (MPC) has demonstrated positive results in equipment control, its application in underground mining operations remains underexplored. To bridge this gap, we aim to investigate and apply MPC methodologies to improve the level of automation and control of mining equipment. Our research will focus on optimizing these control strategies to enhance operational efficiency and reliability in underground mining settings.

2. Neural network optimization method

To develop the timeliness of mine-car dynamic classification, a deep learning neural network is used in this paper to detect process parameters, and the DarkNet-53 network model of YOLOv5 is adopted. YOLO is a typical single-stage target detection algorithm. It uses a convolutional neural network to extract the features of the image target and classify it. It is superior to the R-CNN network in real-time and video processing (Zhang et al. 2016). The DarkNet-53 model of YOLOv5 is expressed in Figure 3. The model uses the bidirectional fusion network structure of "FPN+PAN" and inputs 3-channel 416 × 416 images. The network has a total of 53 convolutional layers, and each convolutional layer performs a convolution operation with a stride of 2. The entire network has a total of 5 dimensionality reductions of 32 times. The convolution of single-layer feature extraction is calculated as follows in Formula (8):

$$G[m,n] = (f \cdot h)[m,n] = \sum_j \sum_k h[j,k] f[m-j,n-k] \qquad (8)$$

The feature layers dimension outputs 416/32 = 13. The neural network final output is a (13, 13, 1024) feature structure (Pu et al. 2021).

To solve the problem of low pixel value detection, high-level and small-resolution feature layers can perform image convolution in a more accurate range. That is, a smaller convolution kernel is used to perform pixel convolution calculations on the image. The detection effect of multiscale pixel changes is optimized, and the target generalization rate is improved.

Inheriting the characteristics of neural network feature layer convolution, the YOLOv5 in this paper is optimized from the FPN network structure, and a new network model, YOLOv5-MINE, suitable for VODP systems is built. The improved network model is shown in Figure 3. The backbone adds a 152 × 152 output layer, and an up-sampling layer is added after the third mapping layer, which is connected to the original network third mapping layer; a new layer from P5 to N5 is added (Shen et al. 2021; Xi et al. 2013; Kong et al. 2014). Correspondingly, the down-sampling Path Aggregation Network (PAN) feature fusion is added, and it is connected to the N4 layer of the original network. The backbone performs up-sampling to increase feature extraction and simultaneously adds feature fusion in the up-sampling part of the FPN layer, and determines the number of layers to increase the feature layer according to the operation structure of the convolution kernel's size. Bottom-up path enhancement is an iterative mapping process, and the iterative endpoint of this process is P5, which corresponds to the new feature map N5 in the PAN. At this time, the structure of FPN+PAN is increased from the original three-layer feature map to the {P2, P3, P4, P5} set map.
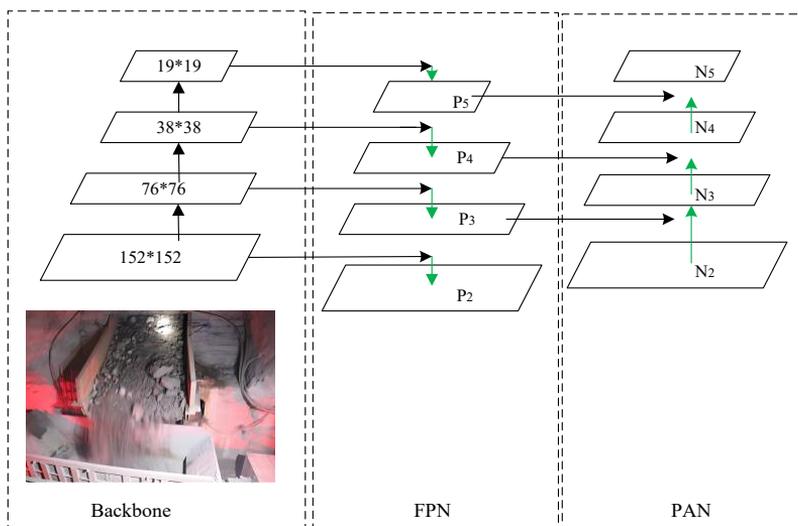

Fig. 3. YOLOv5-MINE network model

Rys. 3. Model sieci YOLOv5-MINE

3. The MPC control method for VODP

3.1. VODP system reference Model

Two cameras installed are parallel to the top edge of the mine car and above the mine car. When the mine car runs to the bottom of the vibrating mining machine, the camera at the upper position detects the mine car. After the target detection, the volume algorithm currently classifies the mine-car status into two categories: empty and full. The ore loading time from empty to full load of each mine car is measured, the timing at the start of ore drawing is t_0, and the time after reaching the predetermined ore loading amount is t_1. The ore height h_1, the cross-sectional area of the minecart is S, and the flow rate is Q, in cubic meters per second. Through the on-site real-time ore loading process in the video monitoring, the ore volume required by each mine-car body from empty to full load and the ore drawing time t of the vibrating ore drawer are measured.

Assuming that the reference model follows the idealized drawing logic, the ore volume value is output according to the neural network, and a volume scatter diagram is developed. The experimental image is as in Figure 4:

The parameters Am and Bm are taken as the first-order parameters, and the controller $u(t)$ is used to linearly fit the $v - t$ scatter plot. The polynomial equation of the fitted rock volume and time is as follows:

$$v_{cnn}(t) = -0.0023t^3 + 0.1685t^2 - 0.2576t + 5.007 \tag{9}$$

Fig. 4. Detecting video key frame images

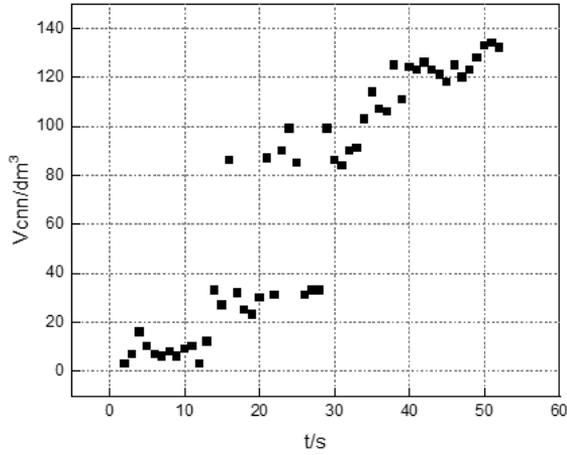Rys. 4. Wykrywanie obrazów klatek kluczowych wideo

Fig. 5. $v - t$ linear fitting function

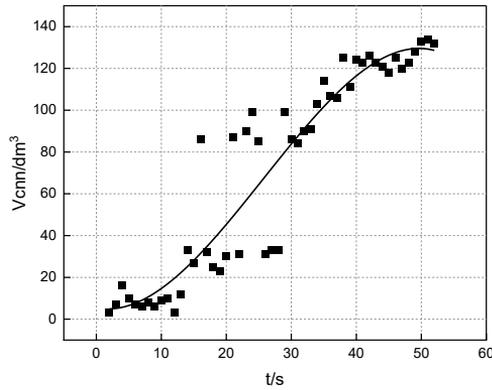Rys. 5. Liniowa funkcja dopasowania $v - t$

Fig. 6. $v - t$ scatter plot

Rys. 6. Wykres punktowy $v - t$

Taking the differential of t on both sides, the relationship between the flow parameters per unit time is obtained:

$$Q(t) = \frac{dv_{cnn}(t)}{dt} = -0.0069t^2 + 0.3370t - 0.2576 \tag{10}$$

Combined with establishing the $Q - v$ relationship and drawing the curve, the mathematical model of the VODP system on the relationship between the flow rate Q and the ore-rock volume v in the mine car is established, which is expressed by the following equation:

$$Q(v) = -0.0009v^2 + 0.1075v - 1.008 \qquad (11)$$

The formula can be solved for the output using the design ideas of the APC controller. The $Q - v$ image is plotted as in Figure 7.
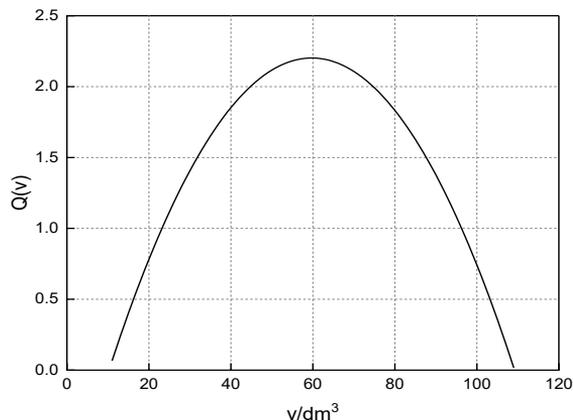

Fig. 7. $Q - v$ function image

Rys. 7. Obraz funkcji $Q - v$

3.2. System controller design

Model predictive control (MPC) solves a finite-time open-loop optimization problem online to obtain a control sequence composed of multiple elements at each sampling interval and applies the first element to the controlled object according to the measured state parameter information of the current system (Yang et al. 2006; Zheng et al. 2014).
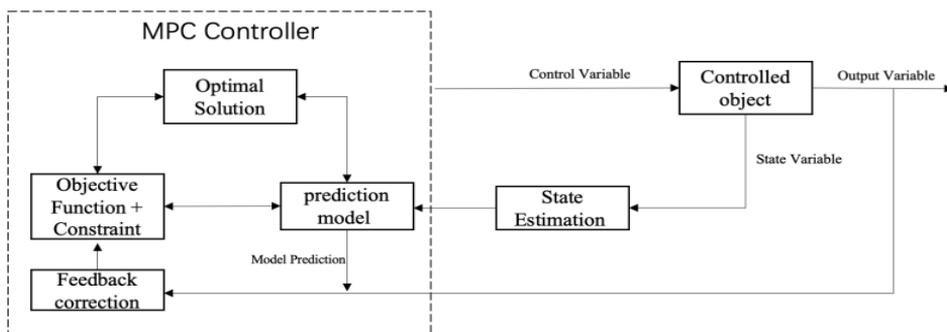

Fig. 8. MPC control block diagram

Rys. 8. Schemat blokowy sterowania MPC

The MPC controller includes three parts: the prediction model, the objective function, and the optimization solution. The MPC controller scroll-optimizes the input based on the prediction model, objective function, and constraints, obtains the optimal control sequence at the current moment, and inputs the first element into the controlled object. The observed value of the state quantity at the current moment is input into the state estimator of the prediction model, and the state estimator estimates the abnormal estimation of the indirect quantity that cannot be directly observed (Wang et al. 2024; Zhang et al. 2022; Wang et al. 2022). The state quantity is re-entered into the MPC controller, and the optimization solution is performed again to obtain the controlled quantity at the next moment. Variables required by the platform are controlled. This cycle constitutes a complete model predictive control process (Yang et al. 2019).

It is assumed that the state equation of the controlled object is:

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) \\ y(k) = Cx(k) \end{cases} \tag{12}$$

In practical engineering applications, there is often a certain error between the predicted value and the actual input value, so the error function $e(k)$ is defined and described by the following formula:

$$e(k) = R_s(k) - Y \tag{13}$$

$R_s(k)$ is the output reference value in the prediction time domain, and the selected quadratic objective function (13) is:

$$J(k) = (R_s - Y)^T (R_s - Y) + \Delta U^T \overline{R} \Delta U \tag{14}$$

The weight matrix of the control amount increment ΔU is used to limit the control amount ΔU to prevent it from being too large. Formula (13) is substituted into Formula (14), and $J(k)$ is further rewritten as:

$$J(k_i) = \left[R_s(k_i) - Fx(k_i)\right]^T \left[R_s(k_i) - Fx(k_i)\right] - 2\Delta U^T \Phi^T \tag{15}$$

$$\left[R_s(k_i) - Fx(k_i)\right] + \Delta U^T \left(\Phi^T \Phi + \overline{R}\right)\Delta U$$

To find the optimal solution, the first derivative is taken, and it is set to zero:

$$\frac{\partial J}{\partial \Delta U} = -2\Phi^T \left[R_s(k_i) - Fx(k_i)\right] + 2\left(\Phi^T \Phi + \overline{R}\right)\Delta U = 0 \tag{16}$$

The optimal solution is solved for the control variable ΔU:

$$\Delta U = \left(\Phi^T \Phi + \bar{R}\right)^{-1} \Phi^T \left[R_s\left(k_i\right) - Fx\left(k_i\right)\right] \tag{17}$$

Through Formula (18) and the optimization method of the predicted value, the optimal solution of the predicted value is obtained as:

$$\Delta U = \left(\Phi^T \Phi + \bar{R}\right)^{-1} \Phi^T \left[R_s\left(v\right) - FQ\left(v\right)\right] \tag{18}$$

4. Case study and practical application

4.1. Case study

At the underground chute, a visual sensing module is installed to extract the features of the mine-car state, and the image data set is annotated. The neural network is trained to verify the optimizations resulting from network training and testing using the YOLOv5-MINE model. The software environment variables used in this experiment are Anaconda + Jupyter Notebook + PyTorch 1.7.1 + CUDA 11.0 + Python 3, and the training graphics card GeForce RTX 2070. Iou_thres = 0.45, and img_size is adaptively adjusted to 640. The number of epoch iterations set in the experiment is 300 times, and the parameter changes of the network output are detected in real time during the training process.

The training and testing results of the improved YOLOv5-MINE network are quantified, and the performance of the target detection algorithm optimization from objective and subjective indicators is evaluated. The learning rate after neural network optimization is calculated using a data set, and the AP parameter curve is measured after 300 iterations.

Arbitrary parameters to measure the training effect of the neural network are based on the recall rate R and the precision rate P of the test set after training. The parameters to measure these are calculated using Formulas (19) and (20):

$$\text{Precision} = \frac{TP}{TP + FP} \tag{19}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{20}$$

For the neural network built in this paper, the PR image drawn during the training experiment is shown in Figure 9.
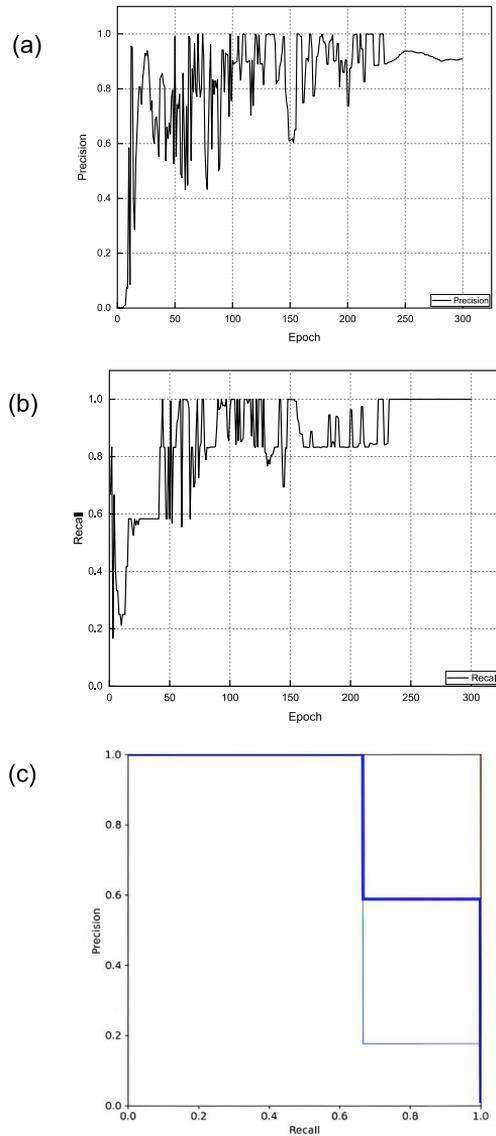
Fig. 9. Training *P–R* curve of the YOLOv5 mine network model: (a) Precision, (b) Recall, (c) *P–R* line

Rys. 9. Krzywa treningowa *P–R* modelu sieci kopalni YOLOv5: (a) precyzja, (b) odwołanie, (c) linia *P–R*

The mAP is a common parameter calculated based on *P* and *R* parameters and used to measure the accuracy of neural networks. According to the output image analysis of the training process, in the previous epoch = 200, mAP gradually reached the termination value of 1. The mAP parameter stabilizes at 1 after 200 iterations.
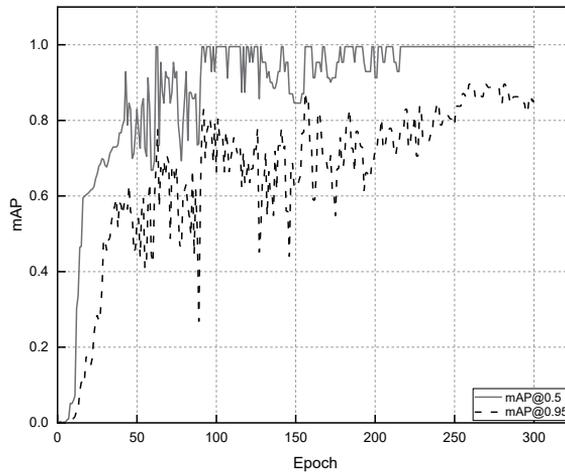
Fig. 10. Variation curve of the mAP parameters after 300 training iterations

Rys. 10. Krzywa zmienności parametrów mAP po 300 iteracjach treningowych

4.2. Controller simulation

MATLAB is used to simplify the integral of $u(t)$ to obtain the system controller $u(t)$. Simulink was used to simulate the entire $APC–OP$ system as in Figure 11.
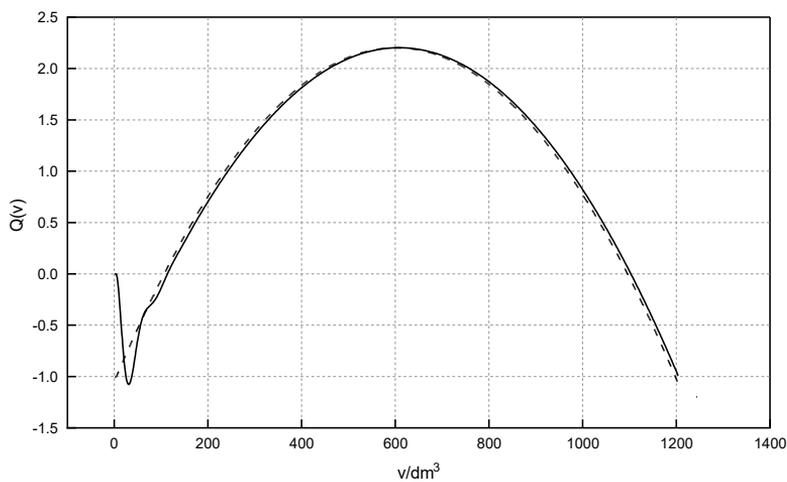

Fig. 11. $APC–OP$ system simulation diagram, the solid line represents the predictive output of the controller, and the dotted line represents the reference model

Rys. 11. Schemat symulacji systemu $APC–OP$, linia ciągła przedstawia predykcyjne wyjście sterownika, a linia przerywana przedstawia model odniesienia

The experimental results show that under the constraints of the controller, the volume of rock in the mine car quickly reaches the set value, the dynamic change increases steadily, and the actual flow value tracks the set value of the reference model well. The ore flow Q of the vibrating ore drawer first increases, reaches the highest value, and then begins to decrease, and finally equals zero when the ore volume v in the mine car reaches the set value. It should be noted that the ore draw flow Q cannot take a negative value in the actual project, but in the experimental image, to show the process of fitting the output to the reference model, the negative part of the image is retained.
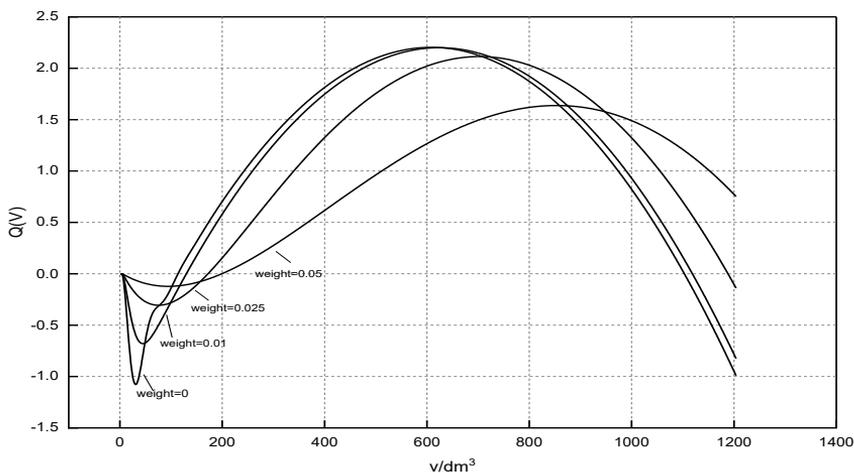

Fig. 12. Simulation effect under different weight parameters, the effects of different weight parameter weights

Rys. 12. Efekt symulacji przy różnych parametrach wagowych, wpływ różnych wag parametrów wagowych

At the same time, in the MPC controller, the effects of different weight parameter weights on the model predictive control are tested. Experimental results show that under the constraints of low weight conditions, the predictor effect is more optimized as the weight value decreases.

4.3. Experimental results and analysis

The underground electric locomotive autonomous driving system is a comprehensive mine production management system aimed at improving transportation efficiency, reducing the number of on-site personnel, and lowering operation and maintenance costs. This system consists of components such as a signal and control system, a control computer system, a video management system, intelligent electric locomotives, tunnel equipment, ore loading and unloading equipment, and an underground network communication and positioning

system. It enables functions such as unmanned/remote/local driving of locomotives and safety warning for locomotives, significantly enhancing mining and transportation efficiency, optimizing production and transportation scheduling, assisting enterprises in rational resource utilization, reducing production costs, and ensuring production safety. This system serves as a crucial support system for the development of unmanned mines, as shown in Figure 13.
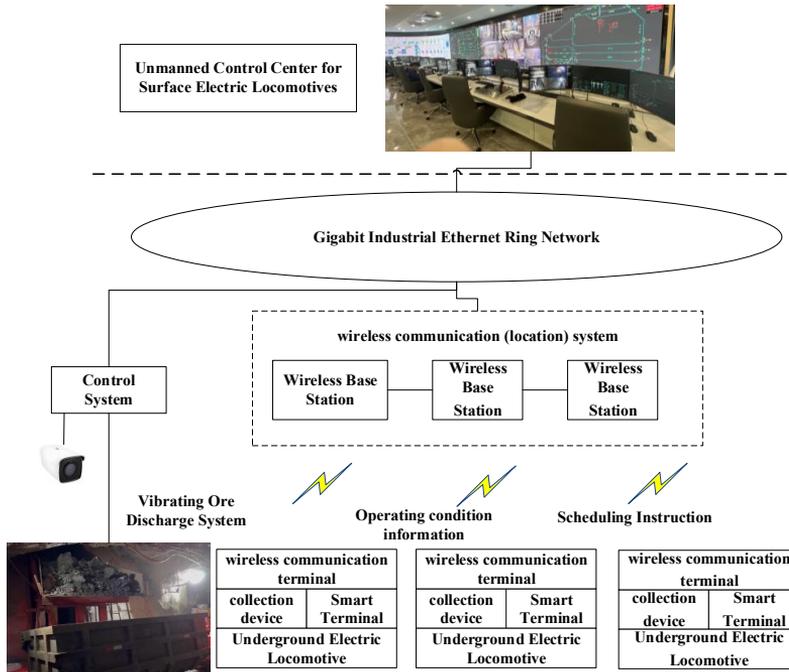

Fig. 13. Diagram of the underground electric locomotive autonomous driving system

Rys. 13. Schemat autonomicznego systemu napędowego podziemnej lokomotywy elektrycznej

This paper presents application testing conducted at an iron ore mine in China. The control flowchart for the fully automatic ore loading control system based on image recognition is illustrated in Figure 14.

The control box at the mine site includes a mining camera, Video AI Computing Unit, Control System, and Switching Equipment. Due to the high humidity and dust levels on-site, the control box is made of stainless steel with an IP67 protection rating. The equipment is installed in a relatively well-ventilated chamber to provide a better on-site environment. The on-site control box communicates with the unmanned control system and the ore discharge control PLC to achieve data exchange, enabling fully automatic operation of the unmanned electric locomotive, as shown in Figure 15.
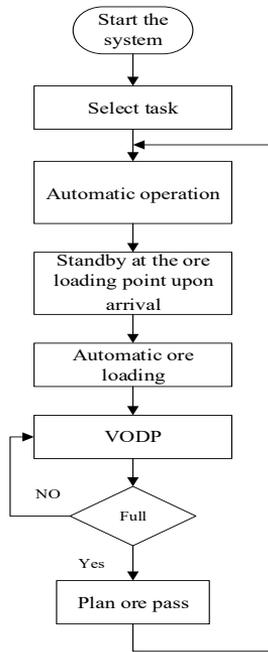
Fig. 14. The control flowchart for the fully automatic ore loading control system

Rys. 14. Schemat blokowy sterowania w pełni automatycznym systemem sterowania załadunkiem rudy

Fig. 15. VODP control interface

Rys. 15. Interfejs sterowania VODP

Through the application of the Visual Perception and Model Predictive Control system, on-site data were collected on ore loading times before and after the application, as shown in Table 2.

Table 2.　Ore discharge time statistics

Tabela 2.　Statystyki czasu rozładowania rudy

No.	Mining time(s) (after VODP control)	Mining time(s) (before VODP control)
1	42.0	45
2	43.0	48
3	46.0	51
4	48.0	49
5	49.0	52
Average	45.6	49

Through on-site testing, the application of the Visual Perception and Model Predictive Control system has eliminated system inefficiencies or stagnation caused by human factors during the ore loading process, resulting in a 6.8% increase in efficiency. When the underground electric locomotive is operated without a driver, and the fully automatic ore discharging system is not applied, one person is required in the ground control room to remotely control one electric locomotive. However, when the fully automatic ore discharging system is applied, only one person is needed to control three or more electric locomotives, reducing the number of operators by at least 50%. The application of project results has significantly reduced the number of underground workers, alleviated labor intensity, and ensured the safe production of the mine.

Conclusion

In this paper, the collaborative ore drawing operation process of an intelligent chute is studied, and the YOLO target detection algorithm with an improved network structure and a high-resolution visual sensor is proposed to build an intelligent collaborative ore drawing system detection module, which is used to detect the dynamic volume of ore rock in a mine car through visual perception measurement. A mathematical model of the collaborative ore drawing system with unknown conditions is proposed, combined with the ore volume parameters collected by vision, and model predictive control (MPC) is applied to dynamically control the ore flow parameters. The practicability of the optimized neural network structure

is verified by comparing the training parameters of the neural network, and the validity of the established system model is verified by the model predictive controller simulation. Field experiments conducted at an iron ore mine in China show that the application of the Visual Perception and Model Predictive Control system eliminates inefficiencies caused by human factors, resulting in a 6.8% increase in ore loading efficiency and a reduction in the need for operators by more than 50%. The proposed system provides a significant advancement in intelligent and unmanned mining operations, enhancing safety, efficiency, and resource utilization.

The Authors have no conflict of interest to declare.

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MODELING AND SIMULATION OF VIBRATING ORE DRAWING PROCESS BASED ON VISUAL PERCEPTION AND MODEL PREDICTIVE CONTROL

Keywords

intelligent mining, vibrating ore drawing process, image detection, MPC

Abstract

For modelling and control of the Vibrating Ore Drawing Process (VODP) in the under-mine rail transportation, a visual perception-based detection method for controlled variables in the drawing process is proposed and applied to the Model Predictive Control for achieving the adaptive draw of the chute. First, the method for estimating ore flow parameters is proposed based on a neural network visual perception method. The neural network-based target detection algorithm is constructed by the well-known DarkNet-53 structure, which is further optimized based on the YOLOv5-MINE structure. Second, the reference model of the VODP system is established by the system identification and data fitting approach. Then, based on this, we use model predictive control to control the system and give a stability analysis of the system with the input and output block diagram under the guidance of the prediction model. Finally, combined with advanced communication technology, simple simulation examples and practical industrial applications are given to illustrate the effectiveness and robustness of the proposed methodology. Field experiments conducted at an iron ore mine in China show that the application of the Visual Perception and Model Predictive Control system eliminates inefficiencies caused by human factors, resulting in a 6.8% increase in ore loading efficiency and a reduction in the need for operators by more than 50%. The proposed system provides a significant advancement in intelligent and unmanned mining operations, enhancing safety, efficiency, and resource utilization.

MODELOWANIE I SYMULACJA PROCESU WIBRACYJNEGO WYCIĄGANIA RUDY W OPARCIU O PERCEPCJĘ WIZUALNĄ I STEROWANIE PREDYKCYJNE

Słowa kluczowe

inteligentne górnictwo, proces wibracyjnego wydobycia rudy, detekcja obrazu, MPC

Streszczenie

W celu modelowania i sterowania procesem wibracyjnego wydobycia rudy (VDOP) w podziemnym transporcie kolejowym zaproponowano metodę detekcji zmiennych kontrolowanych w procesie wydobycia, opartą na percepcji wizualnej, i zastosowano ją do sterowania predykcyjnego modelu w celu uzyskania adaptacyjnego wydobycia zsypu. Najpierw zaproponowano metodę szacowania parametrów przepływu rudy opartą na metodzie percepcji wizualnej z wykorzystaniem sieci neuronowej. Algorytm detekcji celu oparty na sieci neuronowej został skonstruowany w oparciu o znaną strukturę DarkNet-53, która została dodatkowo zoptymalizowana w oparciu o strukturę YOLOv5-MINE. Następnie model referencyjny systemu VDOP został ustalony poprzez identyfikację systemu i dopasowanie danych. W dalszej kolejności na tej podstawie wykorzystano sterowanie predykcyjne oparte na modelu do sterowania systemem i przeprowadzono analizę stabilności systemu za pomocą schematu blokowego wejścia i wyjścia, korzystając z modelu predykcyjnego. Na koniec, w połączeniu z zaawansowaną technologią komunikacyjną, przedstawiono proste przykłady symulacji i praktyczne zastosowania przemysłowe, aby zilustrować skuteczność i solidność proponowanej metodologii. Eksperymenty terenowe przeprowadzone w kopalni rudy żelaza w Chinach pokazują, że zastosowanie systemu percepcji wizualnej i sterowania predykcyjnego opartego na modelu eliminuje nieefektywność spowodowaną czynnikiem ludzkim, co przekłada się na 6-procentowy wzrost wydajności załadunku rudy i zmniejszenie zapotrzebowania na operatorów o ponad 50%. Proponowany system zapewnia znaczący postęp w inteligentnych i bezzałogowych operacjach górniczych, zwiększając bezpieczeństwo, wydajność i wykorzystanie zasobów.