Extension of an Autopilot Model of Shield Tunneling Machines to Curved Section using Machine Learning

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Abstract –

Although a shield tunneling machine should excavate a tunnel along its planned alignment, deviations occur between the planned alignment and the actual result. In this case, the deviating shield machine should return to the planned alignment gradually. However, because controlling the shield machine is difficult and time-consuming, and excavation managers and operators are aging, their skills may be lost in the near future. Artificial intelligence is expected to play an important role in automating the operation of shield tunneling machines, but the method proposed by Kubota et al. and the methods of related studies could not automatically calculate optimum operation parameters for curved sections of the planned alignment. Therefore, in this research, the purpose is to develop an autopilot model, which is a method to automatically calculate optimal operation parameters of the shield machine for straight and curved sections of the planned alignment, based on the method proposed by Kubota et al. Besides, as a result of applying the autopilot model to the data of a previously constructed tunnel, optimal operation parameters could be automatically calculated in the section where the tunnel longitudinal gradient is constant.

Keywords –

Shield tunneling; Shield machine; Automation; Machine learning

1 Introduction

Shield tunneling is a tunnel construction method using excavation machines called shield tunneling machines, and this method is often used for the construction of underground infrastructure, such as sewers and subways [1]. Although a tunnel should be excavated along the planned alignment by shield tunneling, deviations occur between the planned alignment and the actual result [2]. When this happens, the deviating shield machine should return to the planned alignment; however, an abrupt direction change may cause meandering and cracking [3]. In order to gradually decrease the deviation without creating other problems, a target alignment should be generated (Figure 1). However, controlling the attitude and position of shield machines is difficult and time-consuming. Besides, as excavation managers and operators are aging, their skills may be lost in the near future [4]. Thus, it is necessary to automate the operation of shield machines with the same or better accuracy than that of skilled engineers and to improve the accuracy and productivity of tunneling.

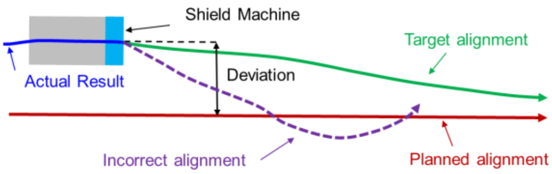

Figure 1. Conceptual diagram of tunnel construction

In order to automate the operation of the shield machine, expectations have been increased for artificial intelligence (AI) to make predictions based on machine learning of huge amounts of data, and research on methods using AI has been conducted. On the other hand, the methods of Iwashita et al. [5], Zhou et al. [6], and Sugiyama et al. [7] have the problem that operation parameters for excavating along the target alignment are determined manually by repeated prediction and evaluation. In addition, Kubota et al. proposed a method to automatically calculate optimal operation parameters of the shield machine for straight sections of the planned alignment [8]. Although there are two types of the planned alignment, one is straight and the other is curved, the proposed method cannot be applied to curved sections of the planned alignment. Therefore, in this research, the purpose is to develop an autopilot model that automatically calculates optimal operation parameters of the shield machine for straight and curved sections of the planned alignment, based on the method proposed by Kubota et al. [8].

2 Literature review

To automate the operation of the shield machine, a method to predict the position and attitude of the shield machines using AI has been proposed. In this chapter, we summarize each method and show the position of this research.

2.1 Related works

In order to automate the operation of the shield machine, expectations have been increased for artificial intelligence (AI) to make predictions based on machine learning of huge amounts of data, and research on methods using AI has been conducted. Although there are two types of the planned alignments, one is straight and the other is curved, Iwashita et al. proposed a method for predicting the shield machined direction for straight sections of the planned alignment and applied it to actual construction data [5]. By repeatedly inputting optimum operation parameters and evaluating the prediction results, this method was able to determine optimum operation parameters without relying on the experience of the operator, and it was confirmed that the accuracy of the tunneling was improved. Zhou et al. proposed a method to predict the position and attitude of the shield machine and applied it to the previously constructed tunnel data [6]. They reported the prediction results of this method can be expected to be used by operators to manually adjust the position and attitude of the shield machine. Sugiyama et al. proposed a method for judging the timing of shield jack operations to propel the shield machine [7]. This method makes it possible to give operation instructions at the appropriate time according to the excavation conditions. The authors proposed a method for automatically calculating optimum operation parameters for straight sections of the planned alignment and have applied the method to the previously constructed tunnel data [8].

In order to improve the accuracy and productivity of tunneling, these methods are required to automatically calculate operation parameters of the shield machine that are predicted to excavate along the target alignment and to use the results in the preparation stage of excavation instructions. However, Sugiyama et al.'s method [7] could not calculate optimal operation parameters, and the methods of Iwashita et al. [5] and Zhou et al. [6] were determined by trial and error through repeated prediction and evaluation. The methods of Kubota et al. [8] and Iwashita et al. [5], as shown in Figure 2, constructed a machine learning model that predicts the amount of difference in the deviation between the planned alignment and the shield machine position, and the shield machine position is predicted by integrating the difference between the predicted deviations. On the other hand, in curved sections of the planned alignment, the amount of difference in deviation differs depending on the curvature, even if the amount of difference in the shield machine position before and after an operation is the same. Therefore, these methods using the amount of difference in deviation as the objective variable has the problem that the shield machine position cannot be predicted accurately in curved sections of the planned alignment.

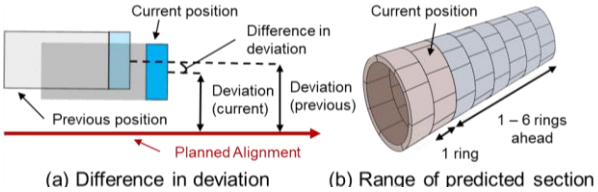

Figure 2. Conceptual diagram of the difference between deviation and predicted section

2.2 Objective of this research

In order to improve the accuracy and productivity of tunneling by using the method for preparing excavation instructions, the purpose of this research is to develop a method for automatically calculating optimal operation parameters for straight and curved sections of the planned alignment, based on the method of Kubota et al. [8]. The method uses a machine learning model that predicts the amount of difference in the position and the azimuthal of the shield machine before and after an operation and automatically calculates optimal operation parameters. Therefore, the method solves the problem of Iwashita et al. [5], Zhou et al. [6], and Sugiyama et al. [7] in automatically calculating optimal operation parameters of the shield machine and the problem of Kubota et al. [8] and Iwashita et al. [5] in applying proposed methods to curved sections of the planned alignment. In addition, the proposed method makes it possible to almost automate the creation of excavation instructions, contributing to the improvement of tunneling accuracy and productivity, and is considered to be a method leading to the automation of the shield machine operation.

3 Methodology

3.1 Autopilot model

In this research, the proposed method automatically calculates optimal operation parameters of the shield machine for straight and curved sections of the planned alignment and uses the prediction results in the preparation of the excavation instructions. The overall picture of the proposed method is shown in Figure 3.

The input data to the proposed autopilot model are sensing data as explanatory variables, and target alignment data. A total of 47 sensing data items were selected as explanatory variables, including operation parameters of the shield machine, items indicating the attitude of the shield machine such as jack stroke and pitching, and items indicating the ground solidity such as propulsive force, articulation pressure, and cutter power. Next, the autopilot model consists of a direction prediction model that predicts the shield machine position using machine learning methods, and an operation parameter optimization model that calculates optimal operation parameters of the shield machine. The predicted positions of the shield machine using the machine learning model are the horizontal, vertical, and azimuthal deviation. The horizontal, vertical, and azimuthal deviations are the deviations in the horizontal, vertical, and azimuthal directions between the tip position of the shield machine and the planned alignment, as shown in Figure 4. The output data from the autopilot model includes operation parameters that are predicted to excavate along the target alignment and the predicted position that the shield machine will achieve. This output data is used as the appropriate values for operation parameters in the excavation instructions.

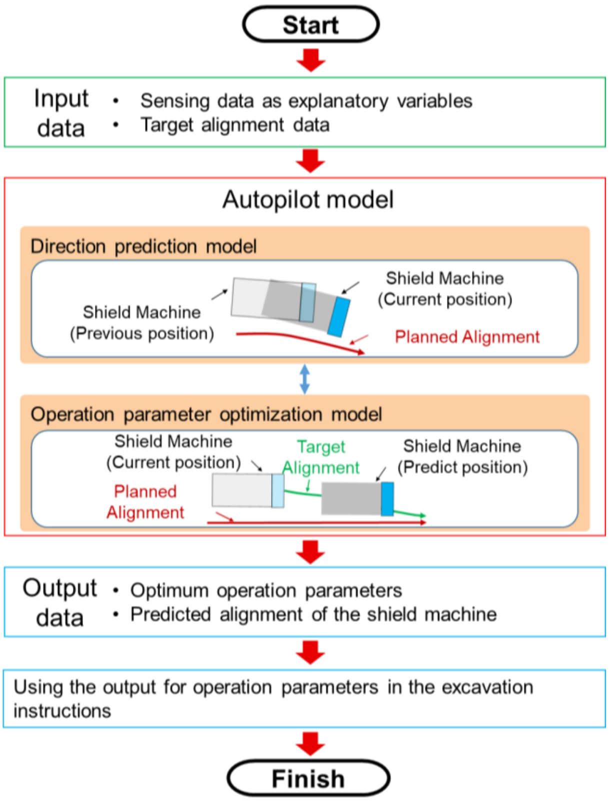

Figure 3. Conceptual diagram of an autopilot model

The autopilot model is intended to assist in the preparation of excavation instructions that include appropriate values for operation parameters. At the construction site, the operator controls the shield machine to get closer to the instructions by carrying out manual surveys for every 4-6 rings of excavation and preparing the excavation instructions based on the results. Therefore, it is assumed that the developed model will be applied to the next construction section, which is 1-6 rings ahead, as indicated in the excavation instructions.

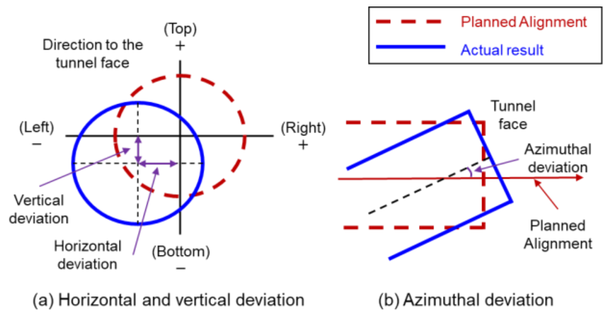

Figure 4. Concept of deviation

3.2 Direction Prediction Model

The direction prediction model that predicts the difference in the position and azimuthal before and after the shield machine operation is proposed for application to straight and curved sections of the planned alignment. In the direction prediction model, a coordinate system is created based on the running direction of the shield machine in both plan and longitudinal views, as shown in Figure 5. The difference in the position of the shield machine at each coordinate is performed by machine learning. Next, the shield machine position can be predicted by integrating the difference in shield machine position after unifying the coordinate systems of the predicted points with the coordinate system of the map.

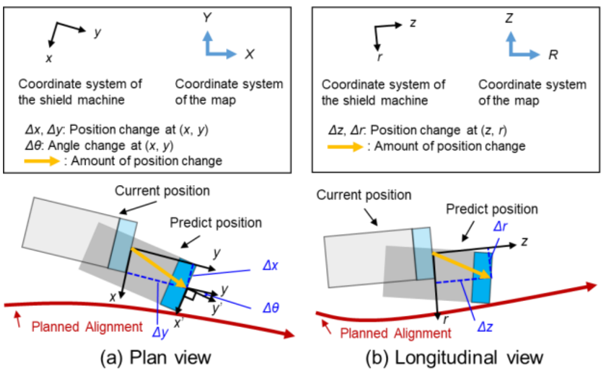

Figure 5. Conceptual diagram of the difference between deviation and predicted section

Machine learning is a field of AI that predicts the shield machine position using a regression method based on machine learning, which predicts a real-valued objective variable from the explanatory variable. Many machine learning regression methods have been developed, such as Support Vector Regression (SVR) [9] and Long Short-Term Memory (LSTM) [10].

The sensing data as explanatory variables in this research are time-series data measured during excavation that is assumed to be susceptible to disturbances. For this reason, we conducted a comparative verification using SVR, which is reported to perform well in the presence of noise, and LSTM, which is reported to perform better than Recurrent Neural Network (RNN) for predicting time-series data [11]. As a result of the comparative verification shown in Section 4, this study adopted SVR, which can predict the position of the shield machine with high accuracy.

When constructing a machine learning model, if the sensing data are used directly, the performance may be adversely affected by noise and the features may not be captured. Therefore, as preprocessing, we applied the processes of differencing and normalization. In the differencing process, the sensing data that represents the meaningful integration value of data difference are converted to a difference from the data obtained during the previous measurement. In the normalization process, a linear regression equation, which transforms the 5% and 95% values of each sensing datum as −0.4 and 0.4, was used. To achieve a range of −0.5 for the lower limit and 0.5 for the upper limit, data below the lower limit of −0.5 were set to −0.5, and data above the upper limit of 0.5 were set to 0.5.

This model predicts the difference in the position and the azimuth concerning the running direction of the shield machine by inputting sensing data as explanatory variables at the current position of the shield machine. However, since the difference in the position is a value in the coordinate system at each predicted point, the coordinate system must be unified in order to obtain the position of the shield machine. Therefore, the shield machine position and deviation between the planned alignment can be predicted by integrating the difference in the shield machine position after unifying the coordinate systems of the predicted points with the coordinate system of the map.

For the developed model, the data measured for each 5 cm jacking stroke of the shield machine was used. This is based on the fact that the minimum height from the faceplate of the shield machine to the cutter bit is typically about 5 cm, which is the minimum height that contributes to directional control.

3.3 Operation parameter optimization model

The operation parameter optimization model automatically generates operation parameters to excavate along the target alignment for each ring using an optimization method. The main optimization methods include genetic algorithms [12] and the particle filter method [13]. The characteristic required for the method to be adopted is the need to prevent delays in construction due to a large analysis time. This study adopted the particle filter method, which has low fluctuations in analysis time, depending on the experimental case, and high processing speed.

The particle filter method estimates the unknown parameters necessary for reproducing the observation data from among the candidate optimal values generated by approximating the shape of the probability distribution using multiple particles (Figure 6). This method can be applied to models where the relationship between the unknown parameters and the observation data is nonlinear. Although the accuracy improves with the number of particles, the amount of computation also increases with the number of particles.

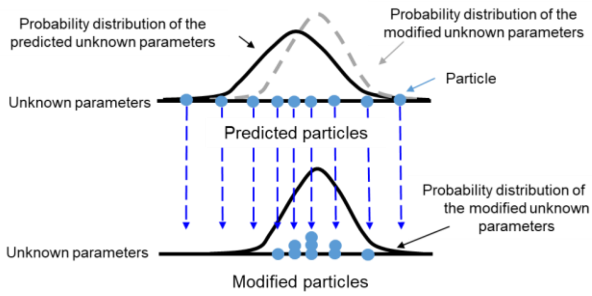

Figure 6. Conceptual diagram of particle filter

Therefore, the unknown parameters are operation parameters and the observation data are deviations of the target alignment. Since it is common practice to use all shield jacks, we decided to use all of them in this model as well. Also, because azimuthal deviations of the target alignment are determined by horizontal and vertical deviations of the target alignment, the observation data are horizontal and vertical deviations of the target alignment. Optimal operation parameters are the one that comes closest to reproducing the horizontal and vertical deviations of the target alignment, which is the observation data, among the candidate optimal values.

On the other hand, in order to predict the shield machine position, explanatory variables other than operation parameters must also be input into the direction prediction model. In the case of calculating optimal operation parameters, the front of the tunnel face is targeted, it is necessary to complement the sensing data as explanatory variables. Among these, the jack stroke data was complemented based on the candidate optimal operation parameters and the data of the jack stroke measured 1 ring earlier. The sensing data used as explanatory variables other than operation parameters and jack stroke were complemented with the same data measured 1 ring earlier, assuming that the influence of the ground was greater than that of operation parameters.

4 Evaluation of Prediction Accuracy

In this Section, in order to predict the arrival position of the shield machine with high accuracy, the machine learning model used to construct the direction prediction model is examined and the prediction accuracy is evaluated. In this verification, we used the data of the "A" project, which was constructed using a slurry shield machine to reduce the damage caused by flooding. There are two types of geology to be excavated in the "A" project. In general, it is known that the behavior of the shield machine differs depending on the ground conditions. Therefore, the direction prediction model was constructed for each geological feature, and the prediction accuracy was evaluated using sensing data measured during excavation of the same geological feature. As shown in Section 2, we used SVR and LSTM as machine learning models to make predictions and compare their accuracy. The sensing data used is shown in Table 1, and the analysis procedure is as follows.

Table 1. Sensing data used in the analysis

Category	Geology I	Geology II
Construction section	Ring Nos. 351-866	Ring Nos. 1117-1616
Geological classification	Alternating strata of diluvial layer, sandy soil and, gravel soil	Alternating strata of diluvial layer and gravel soil

First, the sensing data were divided into training and validation data sets, and the direction prediction model was constructed. Next, the validation data sets were input into the direction prediction model, and the calculated predictions were compared with the measured value. However, assuming the developed model management, the arrival position of the shield machine was predicted 1-6 rings ahead compared with the section where a manual survey was conducted in the section for validation data sets (Figure 7). As shown in Figure 8, 80 % of the sensing data were used as training data and 20 % as validation data, and the data were assigned roles so that both data contained data from straight and curved sections of the planned alignment.

We used the Root Mean Squared Error (RMSE) shown in Equation (1) as the evaluation index for prediction accuracy.

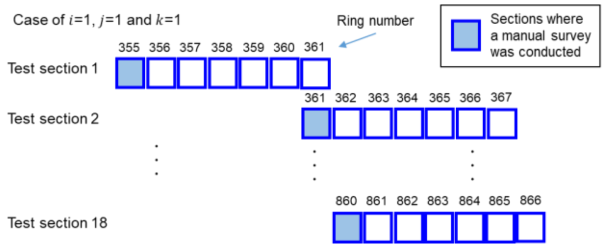

Figure 7. Outline of the section where the verification is conducted

Figure 8. Training data sets and verification data sets

$$RMSE(i,j,k) = \sqrt{\frac{1}{N}\sum_{k}(P(i,j,k,m) - M(i,j,k,m))^2} \qquad (1)$$

where

RMSE(i,j,k): RMSE aggregated under the conditions of i, j and k

N: Number of rings predicted

$P(i,j,k,m)$: Prediction value

$M(i,j,k,m)$: Measured value

i: Difference between the predicted ring number and ring number where manual surveying was conducted (i = 1, 2, 3, 4, 5, 6)

j: Type of deviation (j = 1 for horizontal deviation, j = 2 for vertical deviation, j = 3 for azimuthal deviation)

k: Geological classification (k = 1 for Geology I, k = 2 for Geology II)

m: Predicted ring number.

RMSE is an index of the difference between predicted and measured values squared, averaged, and then aggregated, and the smaller the values, the better the performance. RMSE was adopted because it has the same unit as the predicted value, making it easier to evaluate. Also, the shield machine is constantly excavating an extra 20 mm around the perimeter of the tunnel, which can have a negative impact on the prediction accuracy. Taking the extra excavation into account, the target value was to predict the RMSE within 20 mm for both horizontal and vertical deviations.

The analysis results of horizontal, vertical, and azimuthal deviations of 1-6 rings ahead are shown in

Figures 9 - 11. The smaller the RMSE, the better the performance. For the same experimental case, in most cases, the SVR models were found to be more accurate than the LSTM models in predicting horizontal, vertical, and azimuthal deviations. The SVR models were able to predict the horizontal and vertical deviations within 1-6 rings ahead with an RMSE accuracy of 20 mm or less.

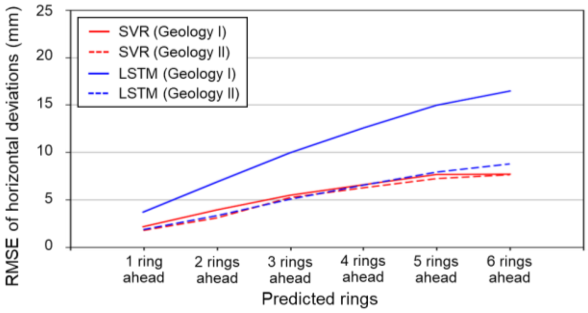

Figure 9. Results of horizontal deviations

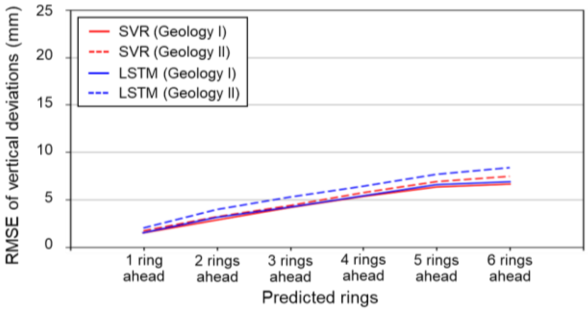

Figure 10. Results of vertical deviations

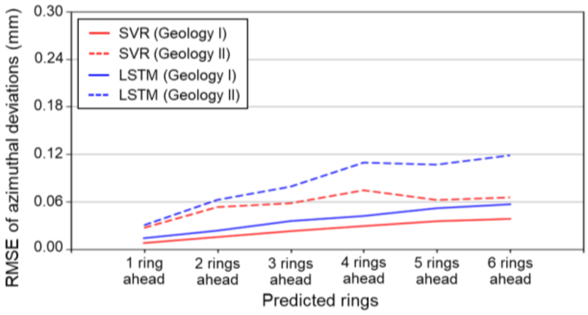

Figure 11. Results of azimuthal deviations

To consider the difference in prediction accuracy among the machine learning models, Figure 12 shows a conceptual diagram of the prediction methods of SVR and LSTM. SVR predicts the deviation based on the previously obtained sensing data, while LSTM predicts the deviation by maintaining a back-and-forth relationship between the sensing data. From these results, it can be concluded that the prediction accuracy of SVR exceeded that of LSTM in the sensing data of the actual tunnel targeted in this verification because the influence of the previous sensing data contributed more to the prediction of the shield machine position than the influence of the back-and-forth relationship between the sensing data. Therefore, in this research, SVR was adopted as the machine learning model used to construct the direction prediction model.

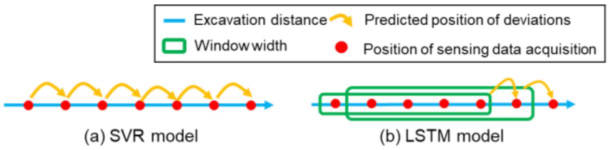

Figure 12. Conceptual diagram of prediction method of SVR and LSTM models

5 Verification Experiment in Previously Construction Section

To show the effectiveness of the developed autopilot model, it was verified whether the deviation between the predicted position of the shield machine and the target alignment position was smaller than the actual measured deviation. The sensing data used is shown in Table 2 and the analysis procedure is as follows.

Table 2. Test data sets used in the analysis

Category	Geology I	Geology II
Construction section	Ring Nos. 867-1048	Ring Nos. 1632-1841
Number of manually surveyed section (longitudinal gradient to predicted section)	32 (Constant) 2 (Change)	49 (Constant) 0 (Change)

First, the direction prediction model was constructed using the sensing data as training data sets. Next, the position of the shield machine was predicted using optimal operation parameters, which were calculated by inputting horizontal and vertical deviations of the target alignment into the autopilot model. The developed autopilot model was applied to the next 1-6 rings compared with the sections where manual surveys were conducted in the prediction section. In the section used as test data, the tunnel longitudinal gradient from manually surveyed sections is constant in some sections and is changing in others. Therefore, the evaluation was divided into two sections: one where the tunnel longitudinal gradient is constant (Case 1) and the other where it is changing (Case 2). The RMSE results for horizontal and vertical deviations were evaluated because the input data to the autopilot model is the target alignment for horizontal and vertical deviations. The analysis results are shown in Figures 13 - 16.

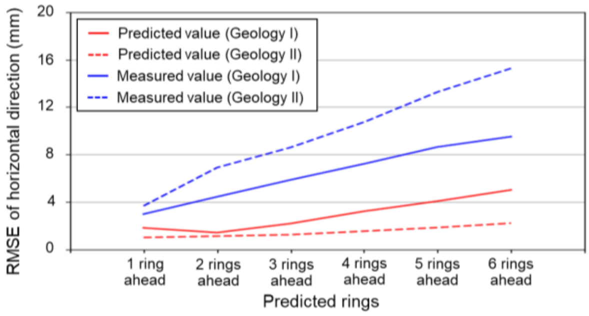

Figure 13. Results of horizontal direction (Case 1)

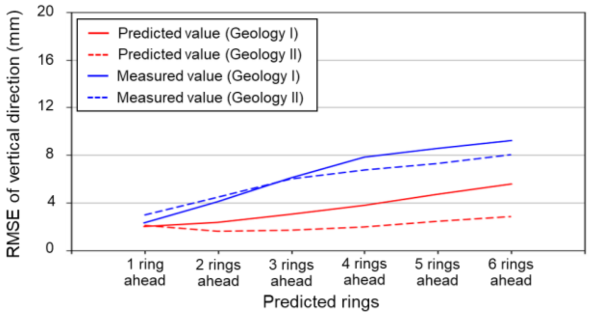

Figure 14. Results of vertical direction (Case 1)

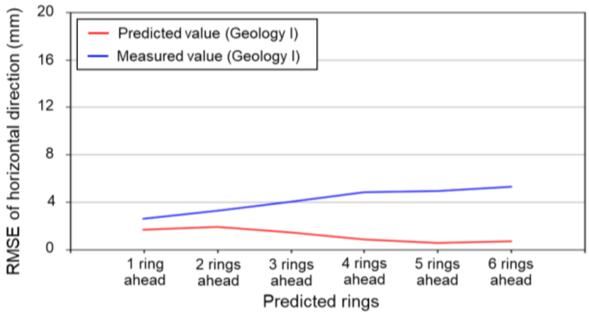

Figure 15. Results of horizontal direction (Case 2)

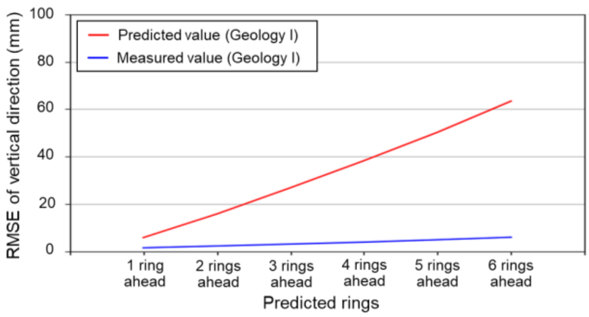

Figure 16. Results of vertical direction (Case 2)

In the section where the tunnel longitudinal gradient is constant (Case 1), the predicted RMSE is smaller than the actual RMSE. On the other hand, in the vertical results of the experimental case, where the tunnel longitudinal gradient is changing (Case 2), the predicted values are larger than the actual values.

In the section where the tunnel longitudinal gradient is changing, it is necessary to change the pitching, which is the angle between the central axis and the horizontal axis of the shield machine shown in Figure 17. In actual practice, the angle of pitching is varied by changing the middle fold angle of the shield machine. In contrast, since the pitching data in the predicted section of the proposed method is complemented with the same sensing data measure 1 ring earlier, it is assumed that the angle of pitching needs to be changed according to candidate optimal operation parameters.

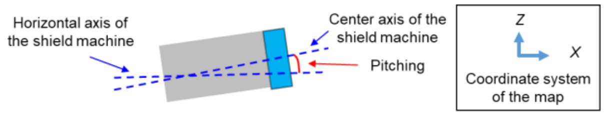

Figure 17. Pitching overview (longitudinal view)

In order to show the validity of this assumption, the results of Case 2 validation are shown in Figures 18 - 19, switching only the pitching data from the same data measured 1 ring earlier to data measured in the excavation of the predicted section. By using the measured pitching data, the RMSE of vertical direction was reduced, and operation parameters were automatically calculated to predict that the excavation would be closer to the target alignment than the actual results. Therefore, in sections where the tunnel longitudinal gradient is changing, correcting pitching data considering the impact of operation parameters may be effective in calculating operation parameters for excavating along the target alignment. In order to expand the method to apply to the section where the tunnel longitudinal gradient is changing, we consider that a machine learning model that predicts the amount of pitching change that occurs in the process of shield machine operation should be constructed and introduced into the proposed method to address this problem.

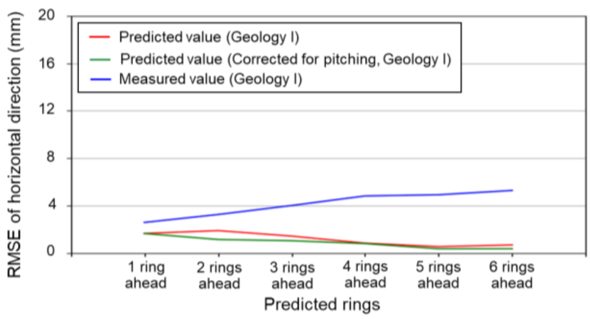

Figure 18. Results of horizontal direction (Case 2: revision)

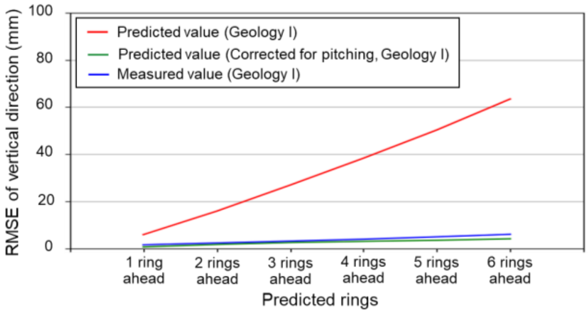

Figure 19. Results of vertical direction (Case 2: revision)

6 Conclusion

This paper proposed a method to automatically calculate optimal operation parameters of the shield machine for straight and curved sections of the planned alignment and to use the prediction results in the preparation of excavation instructions by using machine learning and optimization method, in order to improve the excavation accuracy and productivity of tunnel construction and to contribute to the automation of the shield machine operation. In the section where the tunnel longitudinal gradient is constant, operation parameters for excavating closer to the target alignment than the measured alignment could be automatically calculated by applying the proposed method to the sensing data from a previously constructed actual tunnel. On the other hand, in the section where the tunnel longitudinal gradient is changing, operation parameters for excavating along the target alignment could not be calculated.

As future work, it is necessary to develop and introduce into the proposed method a method for predicting pitching data according to candidate optimal operation parameters and to extend the proposed method to apply to the section where the tunnel longitudinal gradient is changing. Besides, we need to apply the proposed method to unexcavated sections of tunnel construction in progress. The accuracy of the developed model will be improved in the future.

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