Aggregate Weight Prediction Based on Two-dimensional Image Feature Extraction

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Abstract. The weight of aggregates of different particle sizes is vital for the online monitoring of the gradation of asphalt mixtures. In order to complete the online intelligent detection of asphalt aggregate gradation, an automatic coarse aggregate weight prediction algorithm based on the feature extraction of aggregate two-dimensional images is proposed. First, use OpenCV to extract the two-dimensional morphological features of coarse aggregate and use high precision electronic gram scale to obtain the actual weight of the aggregate. Then analyze the correlation between these characteristics and aggregate weight. Finally, the weight of coarse aggregate particles can be accurately predicted by establishing a BPNN (Back-Propagation Neural Network) model. The results show that the weight prediction accuracy of coarse aggregate can be achieved 89.49%. The manual weighing process is reduced, which greatly improves the efficiency of online intelligent detection.

1. Introduction

Aggregate play an important role in skeleton filling of asphalt pavement [1-2]. Different aggregate gradations have different influences on the durability, compactness, ease and other properties of asphalt pavement [3-5]. In general, standard square hole screens with different specifications are used to screen the aggregate morphological granularity so as to obtain aggregate particle size and aggregate gradation parameters, such as the percentage of the weight of a certain screen in the total weight of the sample, the percentage of the screen allowance in the total weight of the sample, etc. The domestic and foreign scholars have achieved some research results in the aggregate morphological features in recent years [6-8].

Li [9] et al. proposed such quantitative evaluation indexes as roughness, convexity, angular parameters and fractal dimension, which can reasonably evaluate the morphological features of aggregate particles. Liu [10] et al. proposed an improved three-dimensional high-resolution image Fourier transform interference detection system for the characterization of aggregate morphology, and verified the rationality of the system by detecting the surface morphology features such as the aggregate's sphericity, flatness ratio, elongation rate and angular. Cao [11] et al. proposed the graham algorithm for convex hull processing of complex images to quickly evaluate the shape features of measured aggregate particles, aiming at the complex shape of aggregate particles and many edges and corners. Wang [12] et al. analyzed the correlation between shape parameter index and gradation, and the results showed that the rectangularity and angular property had a good correlation with aggregate gradation, respectively, and could represent the thickness of mixture gradation. Yang [13] et al. used image-Pro Plus Digital Image processing technology and Digital Tread Depth sensor to obtain the aggregate shape feature index, and established the mathematical model of 2D and 3D shape feature of...
aggregate. Pei [14-15] extracted the relevant 2D features of aggregates, integrated multiple correlation analysis methods, and analyzed the relevant factors that can characterize the shape of the aggregates. And proposed an aggregate particle size calculation model based on neural network algorithm to achieve accurate calculation of coarse aggregate particle size.

The morphological features and weight prediction of aggregates are of great significance. However, there are still relatively few related researches. Therefore, this paper proposes a BPNN model for coarse aggregate weight prediction.

2. Aggregate Feature Extraction from 2D Images

2.1. Image Acquisition and Processing
The aggregate image was collected by the MER-500-14GM camera. The image data format is Mono8 / Mono10. A total of 1000 aggregate images were collected. In order to extract accurate aggregate image features, it is necessary to perform distortion correction, morphological processing and other digital image processing operations on the collected aggregate images. The image processing process is shown in figure 1.

2.2. Aggregate Feature Extraction
The basic features of the aggregate image are extracted, and a total of 30 types of morphological feature information including perimeter, area, circumscribed rectangle and fitted ellipse are obtained, and the original data set of aggregate geometric features is finally established. The schematic diagram of extracting some feature factors such as equivalent ellipse and equivalent rectangle is shown in figure 2.

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Figure 1. Processing of aggregate image.

(a) Circumscribed rectangle

(b) Minimum circumscribed circle.
2.3. Feature Selection
Use Pearson's correlation coefficient to analyze the correlation between the 2D geometric features of different aggregates and the classification of aggregates. The relevant feature factors are obtained as the input of the BPNN model.

3. Aggregate Particle Weight Prediction Based on BPNN

3.1. Establishment of Aggregate Weight Prediction Model
BPNN consists of three layers: input layer, hidden layer and output layer. The input layer receives the data, and the output layer outputs the predict result. The neurons of the first layer connect to the neurons of the next layer, collect the information transmitted by the neurons of the upper layer, and pass the value to the next layer through the activation function. Back propagation learning algorithm is an algorithm to adjust network synaptic weights, so that the actual output of the network is as close to the expected result as possible.

Given m samples \((\hat{X}_h, \hat{Y}_h)\), \(h = 1, 2, ..., m\), the \(\hat{X}_h\) of the \(h\) sample is input into the network, and the resulting network output is \(\hat{Y}_h\), then the objective function of network training is defined as

\[
J = \frac{1}{2} \sum_{h=1}^{m} \left\| \hat{Y}_h - Y_h \right\|^2
\]

To minimize the value of \(J\) in network training, its weight training algorithm can be calculated as

\[
w(t + 1) = w(t) - \eta \frac{\partial J}{\partial w(t)}
\]

Where \(\eta\) is the learning rate.

The aggregate feature data set obtained in 2.2 was taken as samples for model training. The input is mainly the aggregate morphological feature index obtained based on 2D image processing technology, with a total of 19 characteristic factors. The output end is the real aggregate weight. The establishment and training process of BPNN model are shown in figure 3.
Figure 3. Aggregate weight prediction process.

In the process of model construction, the number of layers of the network and the number of neurons in hidden layers should be selected first to determine the structure of the BP neural network model, and the specific values are shown in table 1.

| Parameter name                  | Value range       | Final parameter value |
|---------------------------------|-------------------|-----------------------|
| hidden layer number             | /                 | 2                     |
| hidden layer node               | /                 | 9+13                  |
| output layer activation function | /                 | Sigmoid               |
| learning rate                   | 0.001-0.1         | 0.2                   |
| The number of iterations        | >0                | 700                   |

3.2. Evaluation and Analysis of Experimental Results

The comparison between the measured and predicted weights of 300 aggregates in the test set are shown in figure 4. It can be seen that the prediction result is accurate, and the changes of the two lines are basically the same.

Figure 4. Comparison of test set predicted results.

In order to better quantify the results, $R^2$, MAE (Mean Absolute Error) and MSE (Mean Square Error) can be used as the evaluation indexes of the model prediction results. The formula is as follows:

$$R^2 = \frac{\sum_{i=1}^{N}(y_i - \bar{y})(f_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2 \sum_{i=1}^{N}(f_i - \bar{y})^2}}$$  \hspace{1cm} (3)

$$MSE = \frac{1}{N} \sum_{i=1}^{N}(f_i - y_i)^2$$  \hspace{1cm} (4)

$$MAE = \frac{1}{N} \sum_{i=1}^{N}|f_i - y_i|$$  \hspace{1cm} (5)
Where $y_i$ represents the true value, $f_i$ represents the predicted value, $\bar{y}$ represents the mean value of the sample, $i$ represents the $i$th sample, and $N$ represents the total number of all samples.

The coarse aggregate data sets of four different particle sizes were input as the training set to train the BPNN weight prediction model. The obtained evaluation index value is shown in Figure 5. It can be found that the accuracy of the model trained with a single particle size aggregate as the training set on the test set is significantly lower than the accuracy of all aggregates input into the model for training. The overall prediction accuracy reached 0.8949. At the same time, the MAE of the optimal model is 0.67g, and the MSE is 0.92g.

![Figure 5](image)

**Figure 5.** The R² of aggregate weight prediction models in different training sets.

To verify the validity of the proposed model, the calculation values of the model output are compared with the existing weight calculation methods of aggregate, such as the results of the area-based estimation model and the multiple linear regression model. The comparison result of different methods R² is shown in Figure 6. The proposed BPNN prediction model has the highest prediction accuracy, which is significantly better than other methods.

![Figure 6](image)

**Figure 6.** Performance evaluation comparison with other models.

4. Conclusion

This research has completed the on-line automatic measurement of aggregate weight. By using digital image processing technology to correct image distortion and extract its morphological features, a data set of aggregate features is established. The results show that the weight prediction accuracy of coarse aggregate can reach 89.49%. The proposed automatic prediction algorithm for aggregate weight is of great significance for virtual screening and online grading detection of aggregate.

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