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Fine Structural Characterization of Construction Asphalt Mixtures Based on Image Processing Techniques

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ABSTRACT
The development of economy is inseparable from the construction of traffic buildings. Especially in the current road construction, asphalt mixture is mainly used for pouring. Over time, the asphalt mixture is disturbed by other external factors, resulting in a decrease in the performance of the asphalt mixture. Under this background, this paper mainly studied the mesoscopic angle of the construction asphalt mixture through image processing technology, and analyzed the mesoscopic structural characteristics of the construction asphalt mixture. This paper took the void structure as the research index, and performs image enhancement, image denoising, image sharpening, image segmentation and image edge detection on the collected images of building asphalt mixture in turn. In terms of image enhancement, the image after histogram equalization is clearer in texture, distinct in layers and more prominent than the original image. In terms of image denoising, the median filter method is used, and the noise reduction effect is obviously better than other methods. In terms of image sharpening, the contour of the image sharpened by the Laplacian operator is clearer. In the aspect of image segmentation, the threshold segmentation method has obvious image void boundary and detail information, which is conducive to extracting void information. In terms of edge detection, the image lines under the Canny operator are complete, which greatly reduces the loss of edge information. On this basis, the void structure model was constructed and tested experimentally. The results showed that the average equivalent diameter, average perimeter, and average contour area of the voids in each layer have roughly the same trends as the layers increase. Not only that, the detected void ratio was about 8.14%, which was only 1.17% different from the actual void ratio. This showed that the void structure model constructed under the image processing technology has a significant effect on the porosity detection, and this result brought certain guiding suggestions for the follow-up study of mesostructure characteristics.

Keywords: Image Processing Technology, Asphalt Mixture, Mesostructure Characteristics, Image Denoising, Void Ratio

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1. Introduction

Asphalt mixtures, consisting of coarse aggregate, asphalt mortar (i.e., asphalt binding material and fine aggregate), and voids, are typically non-homogeneous materials that are widely used in pavement construction, such as roadways, tunnels, and bridge decks [1-2]. It is widely recognized that the voids within asphalt mixtures play an important role in resisting major pavement distresses, including rutting, fatigue cracking, low-temperature cracking, and water damage [3-5]. However, in actual construction, pavements are often under-compacted, which results in the actual void ratio of the pavement being greater than the design void ratio [6-7]. Whereas voids are channels for water intrusion, the transport and distribution of water inside asphalt pavements is the root cause of water damage occurrence, which in turn leads to a large number of highways showing a variety of early stage distresses before reaching the design service life [8-10].

However, the traditional assumption that asphalt mixtures are regarded as homogeneous materials has introduced significant bias in the interpretation of compaction mechanism and performance prediction of asphalt mixture construction [11-12]. In addition, it has been shown that the fine structural characteristics of asphalt mixtures can affect the field performance of asphalt pavements under different environmental conditions and vehicle loads, especially the dynamic mechanical response. On this basis, the key to elucidate these effects is to effectively characterize the internal structure of asphalt mixtures [13-15].

In the past few years, cross-scale analysis by combining digital image processing (DIP) and nondestructive testing techniques has been widely applied to characterize the internal fine structure of materials [16-17]. For asphalt mixtures, the fine structure is mainly related to the distribution, orientation and contact of the internal aggregates. The structure consisting of voids is usually characterized by the statistical parameters of the void distribution. Nevertheless, considering the extreme complexity of the fine structure of asphalt mixtures, there is more uncertainty in the selection of the characterization parameters [18-19]. On the one hand, the irregular geometry of voids and aggregate particles makes it impossible to describe them analytically using a single mathematical index, and on the other hand, the curvature of the voids creates great difficulties in their characterization and description [20-21]. Unlike asphalt mortar, which is considered to be a homogeneous viscoelastic material, the inherent anisotropy of the aggregate skeleton and void structure poses a lot of challenges in capturing their properties [22-23]. Therefore, a new characterization system is needed to describe the size distribution and spatial arrangement of aggregate particles and voids.

In the past, most of the research on construction asphalt mixtures stayed on the macroscopic surface, and there was no deep understanding of the mesoscopic characteristics of construction asphalt mixtures. It is not only ineffective to recognize the construction asphalt mixture from the macro level, but also increases the research cost. Under this background, this paper mainly studied and analyzed the microstructure of building asphalt mixture through image processing technology. The relationship between the characteristics and the macro performance of construction asphalt mixture was explored, and the mesoscopic mechanism of construction asphalt mixture is recognized from a new perspective.

2. Meso-structural Properties of Building Asphalt Mixture

2.1. *Construction Asphalt Mixture*

Construction asphalt mixture is a mixture of different aggregates and asphalt, which is mainly composed of asphalt, aggregate and mineral powder. With the in-depth research on the internal structure of building asphalt mixture, there are mainly two theories of surface theory and mortar theory. Its theoretical structure is shown in Figure 1:

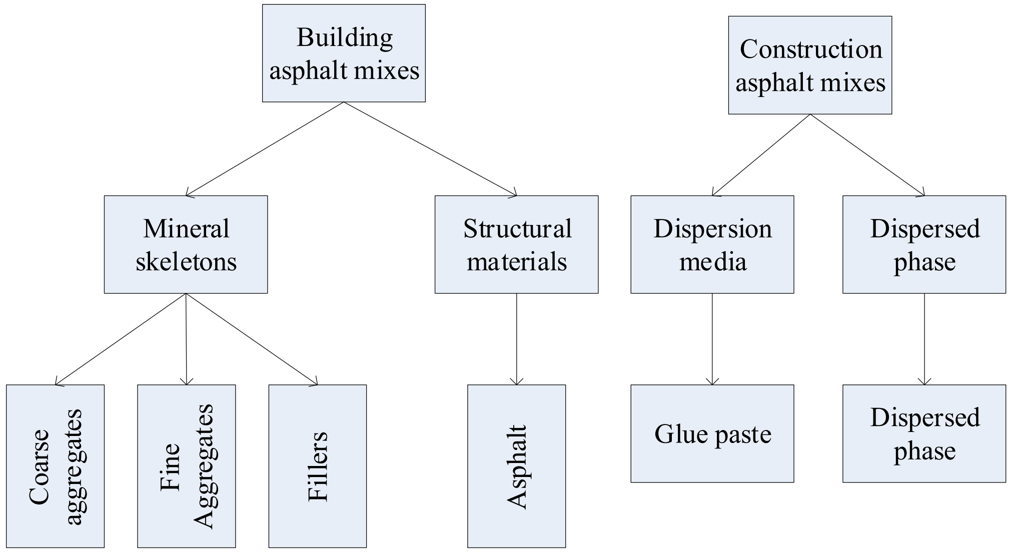

Fig. 1. Diagram of two different theoretical structures for construction asphalt mixes

According to the relevant information, the adhesion between the asphalt mortar and the surface of the mineral material determines the adhesion of the construction asphalt mixture. The macroscopic features of building asphalt mixtures are related to the differences in their internal mesostructures. Only a stable structure can improve the strength of construction asphalt mixture, so we need to analyze the characteristics of the mesoscopic structure of construction asphalt mixture.

2.2. Voids in Construction Asphalt Mixture

The gas in the common construction asphalt mixture is generally divided into two types: connected gas and closed gas. Among them, the voids of connected gases affect the water permeability and other functions of the building asphalt mixture, while the voids of closed gases affect the strength of the building asphalt mixture. If the void ratio is large, when the building is subjected to a certain pressure, the internal pressure of the material would increase. After the external pressure is over, the internal pressure of the material decreases sharply, and the repeated changes in the pressure would cause the asphalt to separate from the aggregate, resulting in cracks on the building surface. Therefore, we must ensure the void size of the building asphalt mixture to ensure the safety of the building. Its void type is shown in Figure 2:

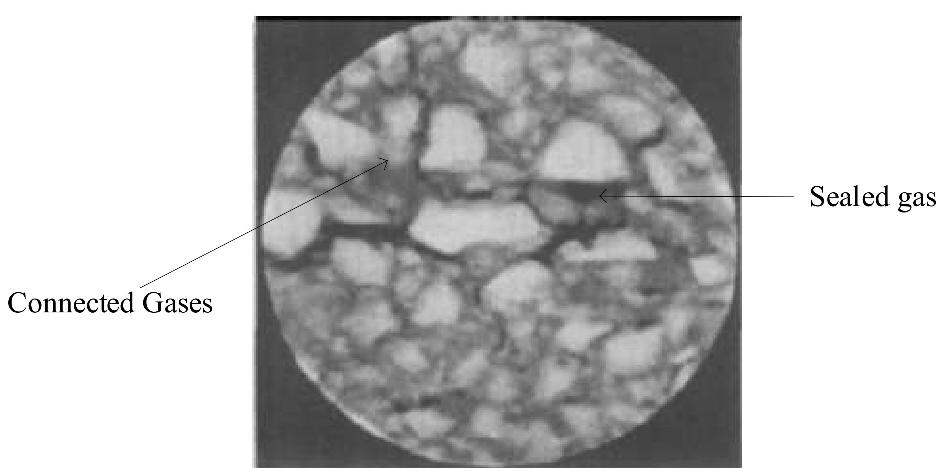

Fig. 2. Types of voids in construction asphalt mixes

After we theoretically discuss the voids of construction asphalt mixtures, we need to measure and analyze the voids of the materials. This paper mainly measures data from two aspects: macroscopic and microscopic:

1) Macroscopic measurement of void ratio. In this paper, the surface dry method is generally used for macroscopic determination of voids. The basic principle of the surface dry method is to study the sum of the closed void volume within the material and the total open void volume of the internal communicating surfaces as the ratio of the gross volume in the overall structure of the material. The operation of this method is to first remove the aerosols on the surface of the material, then weigh the mass m_a of the material in the air in a dry environment, secondly measure the mass of the material in water m_b, and finally measure the surface dry mass of the material m_c. Its calculation formula is as follows:

$$\rho_c = \frac{m_a}{m_c - m_b} \tag{1}$$

ρ_c is the relative density of the material volume.

2) Mesoscopic measurement of porosity. The porosity of the material was calculated and analyzed by the surface-drying method before, but the surface-drying method may have problems such as non-standard wiping of the material during operation, resulting in inaccurate measurement results. All void measurements from the macroscopic scale are of little significance, and the composition of building asphalt mixtures is complex. We can use image processing technology to process two-dimensional and three-dimensional cross-sectional images of the material while keeping the material structure unchanged, so as to accurately and intuitively understand the internal structure and characteristics of the material. On this basis, this paper mainly uses relevant image acquisition tools to acquire images of building asphalt mixtures. Then, image processing tools are used to obtain the internal mesostructure information of the material, and finally the porosity of the material is calculated by the DPI method. Its calculation formula is as follows:

$$i = \frac{\varphi_a}{\varphi_b} \tag{2}$$

Among them, i is the void ratio of the building asphalt mixture, φ_a is the number of void pixels in the cross-sectional image of the building asphalt mixture, and φ_b is the overall number of pixels in the cross-sectional image of the building asphalt mixture.

3. Introduction to Image Processing Technology

Construction asphalt mixture is mainly composed of aggregates, asphalt and voids, and the mixture is mainly divided into material properties and structural properties. In the current road construction, the macro-mechanical properties of building asphalt mixture are controlled by its meso-structure, which is difficult to observe and analyze with the naked eye. On this basis, this paper mainly conducts an in-depth analysis of the meso-structural characteristics of building asphalt mixtures through image processing technology.

3.1. Image Enhancement Technology

Image enhancement is a way of human intervention to improve image quality. Each image enhancement method has its specific application range, and different methods also have certain differences in the results of processing the same image. Therefore, image enhancement is a process of comparison and selection. A variety of methods are used to process and compare images to find the best method for enhancement.

Histogram equalization mainly converts the brightness value of the grayscale image to the image to be processed. It makes the transformed image appear evenly distributed, and redistributes the pixel values of the entire image. In this process, although the gray value distribution of the original digital image is changed, the spatial position of each pixel is not changed. Then, after the image correction is performed by the histogram, the grayscale interval of the image is widened, and the contrast is increased, and finally a clearer image effect is obtained than the original image. In this paper, the construction asphalt mixture is processed mainly through histogram equalization, and its operation is mainly divided into 4 steps:

Step 1: Calculate the grayscale histogram of the original digital image, the formula is as follows:

$$p_i(q_i) = \frac{m_i}{m} \tag{3}$$

Among them, m is the total number of pixels in the digital image; m_i is the total number of pixels of gray value i.

Step 2: Calculate the cumulative grayscale histogram in the original digital image, and the calculation formula is as follows:

$$n_i = \sum_{j=0}^{j} \frac{m_i}{m} \tag{4}$$

Step 3: Calculate the gray level after mapping, and its calculation formula is as follows:

$$b_i = \text{int}\left[(N-1)n_i + 0.5\right] \tag{5}$$

Among them, int is the integer value, and N is the number of gray levels in the original digital image.

Step 4: Determine the mapping relationship between q_i and b_i, perform pixel grayscale transformation according to this relationship, and then count the number of pixels of each grayscale after the transformation, and calculate a new histogram.

We now select an image of a building asphalt mixture and perform the above operations on it to obtain relevant data results. The results are shown in Figures 3 and 4:

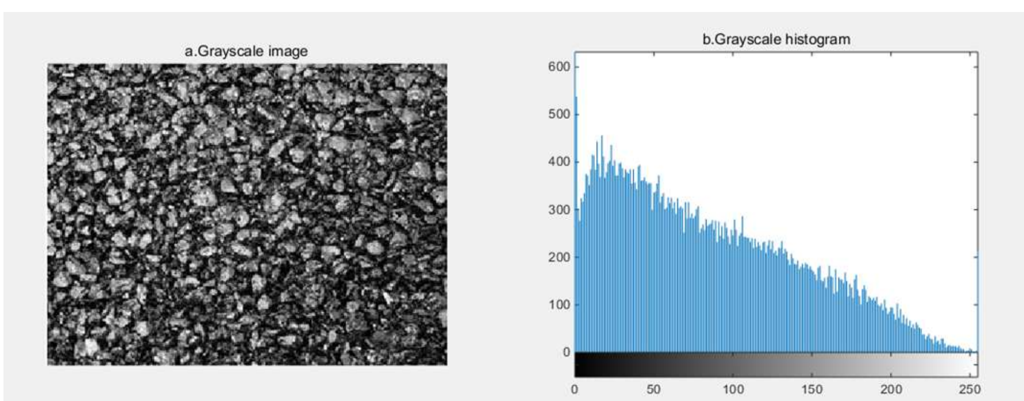

Fig. 3. Grayscale images and grayscale histograms of construction asphalt mixes

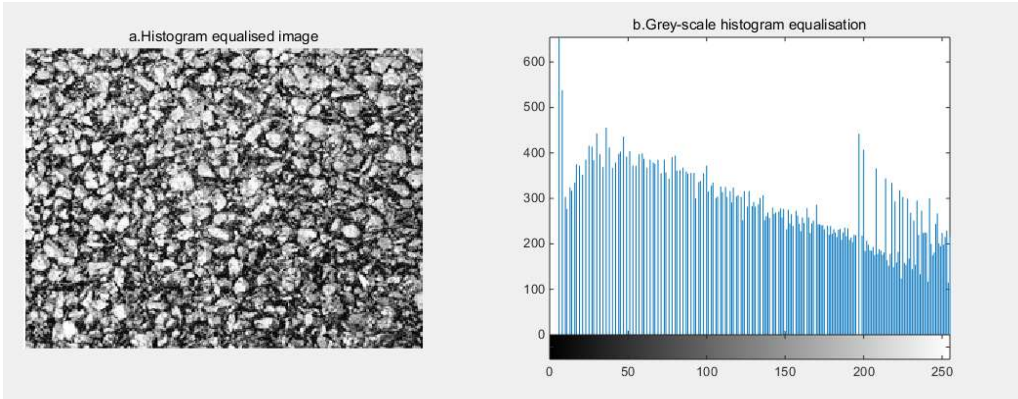

Fig. 4. Grayscale images and grayscale histograms of construction asphalt mixes after histogram equalization

As can be seen from Figure 3, the grayscale image texture of the building asphalt mixture is not clear enough. The distribution of its grayscale histogram is not uniform enough, and the histogram is in a state of being too aggregated. This shows that the image information of building asphalt mixture is not rich and the structure is not complete enough. It can be seen from Figure 4 that after the histogram equalization of the building asphalt mixture, the image texture structure is clearer than the original image, and the histogram is more scattered. Compared with the original histogram, the image has distinct layers and is expanded left and right, which makes the information of the original image more prominent and the clarity improved.

3.2. Image Denoising

In the process of obtaining construction asphalt mixture, we are interfered by other factors, making the image information incomplete. This is not conducive to our extraction and analysis of the key information of the image, especially in the mesoscopic image research of building asphalt mixture, the interference of image noise would seriously affect the research and analysis of its mesoscopic characteristics. Therefore, before we analyze the image, we need to denoise the image. In this paper, the median filtering method, the mean filtering method and the Wiener filtering method are mainly used to denoise the building asphalt mixture image:

1) Median filter method. The principle of median filtering is a nonlinear image processing technology that uses sorting theory for noise reduction. The process is to replace the target gray value with the median value of the gray value of other pixels in the area similar to the target gray value. Its calculation formula is as follows:

$$x_{ij} = med\left\{ y_{i+m,j+n}, (m,n) \in A, (m,n) \in X^2 \right\} \tag{6}$$

Among them, A is the filter window size.

2) Mean filter method. The essence of the mean filter method is to define a template for the target pixel, and then take the average value of the template covering the surrounding pixels to replace the target pixel, and finally achieve the effect of image smoothing. This article takes the 3×3 template as an example to introduce, assuming that there is a pixel value $f(i,j)$, and its related expression is as follows:

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \tag{7}$$

$$average = \frac{1}{9}(f(i-1, j-1) + f(i, j-1) + f(i+1, j-1) + f(i-1, j) + f(i, j) + f(i+1, j) + f(i-1, j-1) + f(i, j+1) + f(i+1, j+1)) \tag{8}$$

(3) Wiener filter method. Wiener filtering is essentially a least-squares filtering method by reducing the mean error between the original image and the processed image. Its calculation formula is as follows:

$$\varepsilon^2 = \min E\left\{\left[f(i,j) - \hat{f}(i,j)\right]^2\right\} \tag{9}$$

After the relevant theoretical discussion of image noise reduction, we applied the above denoising methods to the noise-containing building asphalt mixture images, and compared the image denoising effects of different methods. The image processing result is shown in Figure 5:

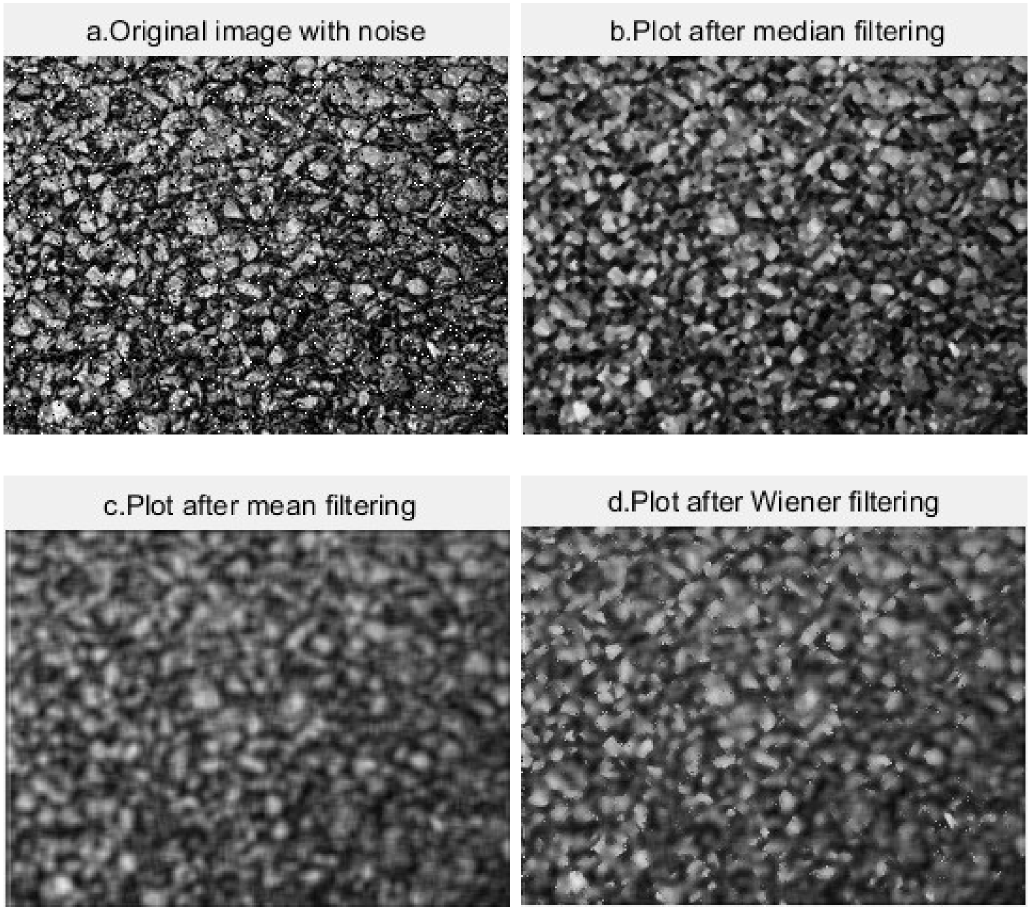

Fig. 5. Comparison chart of the effect of different noise reduction methods

It can be seen from Figure 5 that after different methods are used to process the image containing noise, the image noise reduction methods in Figure 5(b)-(d) are median filtering method, mean filtering method and Wiener filtering method in turn. Among them, the texture structure of the mixture in the processed image in Figure 5(b) is clear, and the noise reduction effect is obviously better than other methods. However, the images in Figure 5(c) and (d) have poor noise reduction effect, the entire image outline is blurred, and the edge information is not complete enough. In this paper, the median filter method is selected to denoise the images of building asphalt mixtures.

3.3. Image Sharpening

In the process of denoising the image, the edge information of the image would inevitably be blurred to a certain extent. This would cause the lack of image information. Image sharpening is to use differential operation to enhance the gray-scale transition part of the image, thereby achieving the purpose of enhancing the target contour and edge information. Therefore, we need to sharpen the image. This paper mainly selects the Laplacian operator to sharpen the image. Its calculation formula is as follows:

$$\nabla^2 f(x,y) = \frac{\partial^2 f}{\partial m^2} + \frac{\partial^2 f}{\partial n^2} \tag{10}$$

Now, the image of building asphalt mixture is sharpened, and the sharpened image is shown in Figure 6:

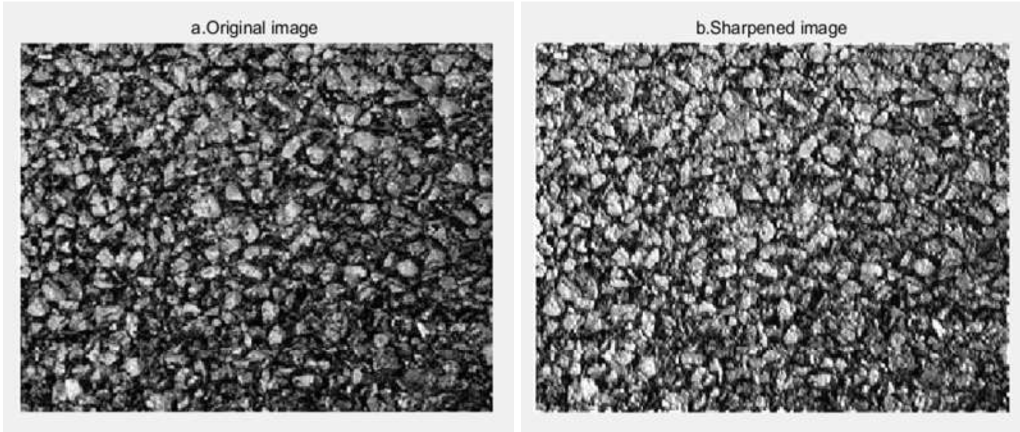

Fig. 6. Image comparison of construction asphalt mixes before and after sharpening

It can be seen from Figure 6 that the image outline of the building asphalt mixture sharpened by the Laplacian operator is clearer than the original image, and the blurriness is reduced. This shows that the image effect after sharpening by the Laplacian operator is significant.

3.4. Image Segmentation

After the above-mentioned related image processing work, we need to extract the key information of the image. In the process of analyzing the image information, we would not analyze all the information of the image. In the image information of the entire building asphalt mixture, we only need to extract its meso information, so we need to segment the selected image. In terms of image segmentation, there are mainly state method, iterative method, watershed algorithm and threshold segmentation method. This paper mainly selects the threshold segmentation method to segment the image.

We base our research on the grayscale histogram of Figure 3. Assuming that there is a segmentation threshold n, the grayscale histogram of Figure 3 is divided into two regions, namely a and b. The grayscale expressions of the two regions are as follows:

$$\alpha_a = \sum_{i=0}^{n} \frac{x_i}{x} \tag{11}$$

$$\alpha_b = \sum_{i=j+1}^{N-1} \frac{x_i}{x} \tag{12}$$

$$\beta = \sum_{i=0}^{N-1} f_i \times \frac{x_i}{x} \tag{13}$$

$$\beta_a = \frac{1}{\alpha} \sum_{i=0}^{n} f_i \times \frac{x_i}{x} \tag{14}$$

$$\beta_b = \frac{1}{\alpha} \sum_{i=j+1}^{N-1} f_i \times \frac{x_i}{x} \tag{15}$$

Among them, α_a and α_b are the area ratios of regions a and b, respectively, β is the average gray level of the image, β_a and β_b are the average gray levels of regions a and b, respectively, and N is the number of gray levels of the region. When the gray levels of the two regions are very different, the results between β_a, β_b and β of the two regions would also be very different. The variance formula between the regions is as follows:

$$\delta^2 = \alpha_a(n)\left[\beta_a(n) - \beta\right]^2 + \alpha_b(n)\left[\beta_b(n) - \beta\right]^2 \tag{16}$$

When the regional variance difference between regions a and b is the largest, it can be considered as the best segmentation state, and its threshold expression is as follows:

$$T = \max\left[\delta^2(n)\right] \tag{17}$$

On this basis, this paper first obtains the best segmentation threshold of the image, and then uses the threshold to segment the image. The segmentation diagram is shown in Figure 7:

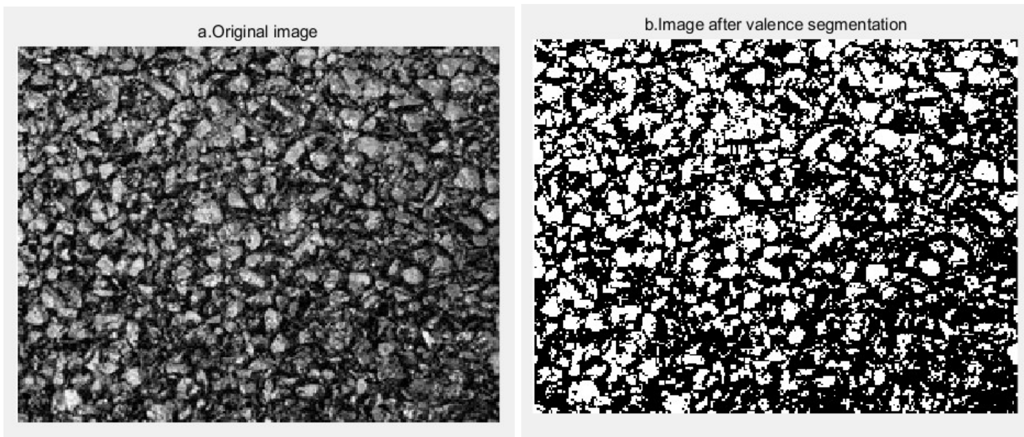

Fig. 7. Comparison of splitting results

As can be seen from Figure 7, the segmentation effect of the image is good, and the gap boundary and detail information of the segmented image are obvious. This paper mainly extracts the void information from the entire image background, which is convenient for subsequent work.

3.5. Edge Detection

An edge is a collection of gray-scale discontinuous pixels in an image. Collections of pixels scattered between adjacent regions in an image make up the edges of the image. In this paper, the Canny operator is mainly selected to perform edge detection on the image of building asphalt mixture. Its calculation formula is as follows:

$$F(i,j,\varepsilon) = \frac{1}{2\pi\varepsilon^2}\exp\left(-\frac{i^2+j^2}{2\varepsilon^2}\right) \tag{18}$$

$$M(x,y) = N(x,y) \times F(i,j,\varepsilon) \tag{19}$$

Among them, $N(x,y)$ is the original image, ε is the scale parameter, F is the gradient magnitude, and $M(x,y)$ is the smoothed data array. According to this theory, edge detection is performed on the original image, and the detection results are shown in Figure 8:

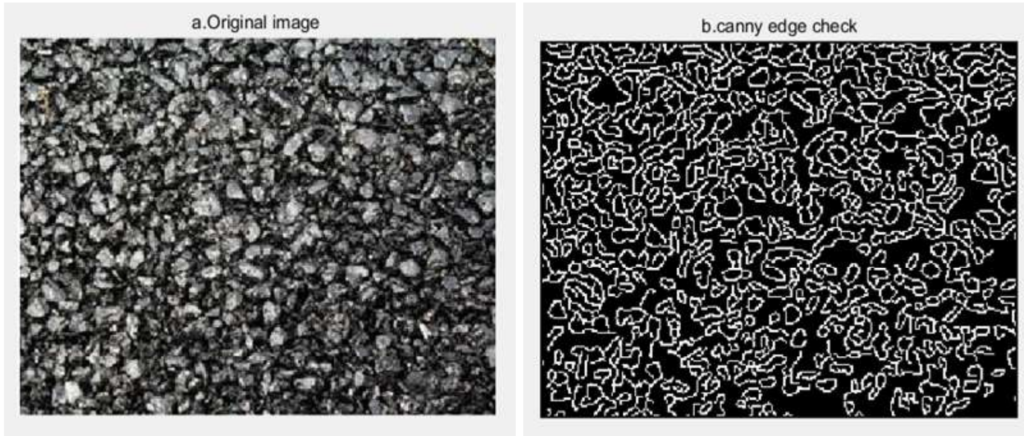

Fig. 8. Canny edge detection rendering

As can be seen from Figure 8, after the edge detection of the Canny operator, the contour of the image is more clear and obvious. The phenomenon of edge interruption in the detection process is also reduced, and a relatively complete line is obtained, which fully reflects the edge information of the image.

4. Experiment of Void Space Structure Model

4.1. Model Design of Mesoscopic Characteristics Based on Image Processing Technology

The internal structure of the building asphalt mixture has been described. Due to the influence of factors such as segregation in the production process of building asphalt mixture, the internal structure of the material appears uneven. Simply put, the distribution of voids in the construction asphalt mixture is irregular. The meso-geometry of voids and their spatial distribution have a crucial impact on the performance of building asphalt mixtures. Therefore, on the basis of image processing technology, this paper focuses on analyzing the void structure of building asphalt mixture.

When the model is constructed, we need to extract the corresponding three-dimensional information from the building asphalt mixture. Real reproduction of forms such as voids and aggregates can be realized, so that the internal structure information in the building asphalt mixture can be expressed intuitively. Before extracting the three-dimensional information of the building asphalt mixture, we need to perform image enhancement, image de-noising and other technical processing to obtain the void information in the building asphalt mixture. Finally, a three-dimensional stereoscopic image of the void is obtained. The construction of the 3D model of the void is mainly divided into 4 steps:

Step 1: input the image of the processed asphalt mixture, which is convenient to extract the three-dimensional information of the mesostructure of the void.

Step 2: Identify each void contour pixel in the processed image by the void contour detection method, and obtain its corresponding void contour entity model. A mapping between each void contour pixel and the corresponding void contour solid model is established.

Step 3: Each void contour pixel corresponds to the void contour entity modeling, and finally uses Skinning to obtain the latest single void entity model of the BODY type.

Step 4: input the newly obtained single void solid model, and construct the solid model of the void space structure through ACIS.

4.2. Geometric Characteristics and Distribution of Voids

In the front, we first processed the image of building asphalt mixture with related technology, and then extracted its void structure information through the processed image and built the corresponding model. To check the usefulness of the model, we conduct analysis on the designed model. This paper starts with the three-dimensional structural characteristics of voids in building asphalt mixtures. In this experiment, all the data are obtained from the correlation processing of building asphalt mixture images.

Combined with relevant data, we select multiple indicators that can describe the geometric characteristics of voids based on the previous analysis and processing of the image, and then perform statistical analysis on the parameters of the selected indicators. Its parameters can describe the three-dimensional structure of the void. This paper takes the construction asphalt mixture (CAM) specimen as the research object. The CAM specimen was formed by the Superpave rotational compaction method, the moulding parameters are displayed in Table 1:

Table 1. Specimen forming parameters table

Cumulative pass rate (%)	19.18	12.14	9.42	4.81	2.34	1.05	0.63	0.32	0.15	0.07
Sieve hole size	100	90.1	87.35	48.1	27.9	18.1	12.5	9.7	6.8	5.2
Volume content of voids (%)	9.31									

4.3. *Three-dimensional Geometric Features and Distribution of Voids*

Now, the equidistant image acquisition work is carried out on the construction asphalt mixture specimen, and then it is processed through void contour identification and parameter statistical analysis. According to the above statistical analysis results, the void-related geometric parameter data of a single image are obtained, as shown in Table 2:

Table 2. Data for each parameter of the three-dimensional characteristics of the void

Gap Serial Number	Equivalent diameter(mm)	Circumference (mm)	Area (mm2)
1	2.12	3.71	4.21
2	2.21	3.89	4.53
3	2.39	4.21	4.89
4	2.88	5.87	5.12
5	3.01	6.51	7.13
6	3.11	6.96	6.54
7	4.41	10.21	13.25
8	4.87	12.12	16.87
9	5.21	12.89	21.12
10	6.10	13.43	27.98
...	...	...	...
100	11.11	30.10	98.32

From Table 2, we can see the parameters of the equivalent diameter, perimeter and area of the void in a single image, but it is difficult to accurately understand the three-dimensional feature information of the void. In order to better carry out experimental research and analysis, we carried out continuous image acquisition work on the specimen with an interval of 1 mm, and statistically analyzed the value of each parameter of the void. The upshots are displayed in Table 3:

Table 3. Table of values for each parameter of the voids in the different layers

Layer number	Number of profiles	Average equivalent diameter(mm)	Average circumference(mm)	Average profile area (mm2)	Void ratio (%)

1	120	2.81	6.99	9.81	6.15
2	135	3.62	8.10	15.1	6.51
3	140	3.61	7.98	14.56	6.21
4	180	4.12	10.21	20.12	7.13
5	191	3.31	10.67	21.01	7.32
6	210	3.55	8.81	16.16	8.38
7	220	3.75	9.11	16.21	10.32
8	231	3.65	8.21	13.98	9.39
9	222	3.10	7.12	11.21	8.61
10	238	3.12	7.31	10.25	8.82
11	218	3.76	8.51	12.31	10.21
12	201	3.29	7.34	10.68	8.68

For the data in Table 3, we carried out a graph analysis of the average equivalent diameter, average perimeter, average contour area and porosity, respectively, to analyze the relationship between different index parameters and layers. The result is shown in Figure 9:

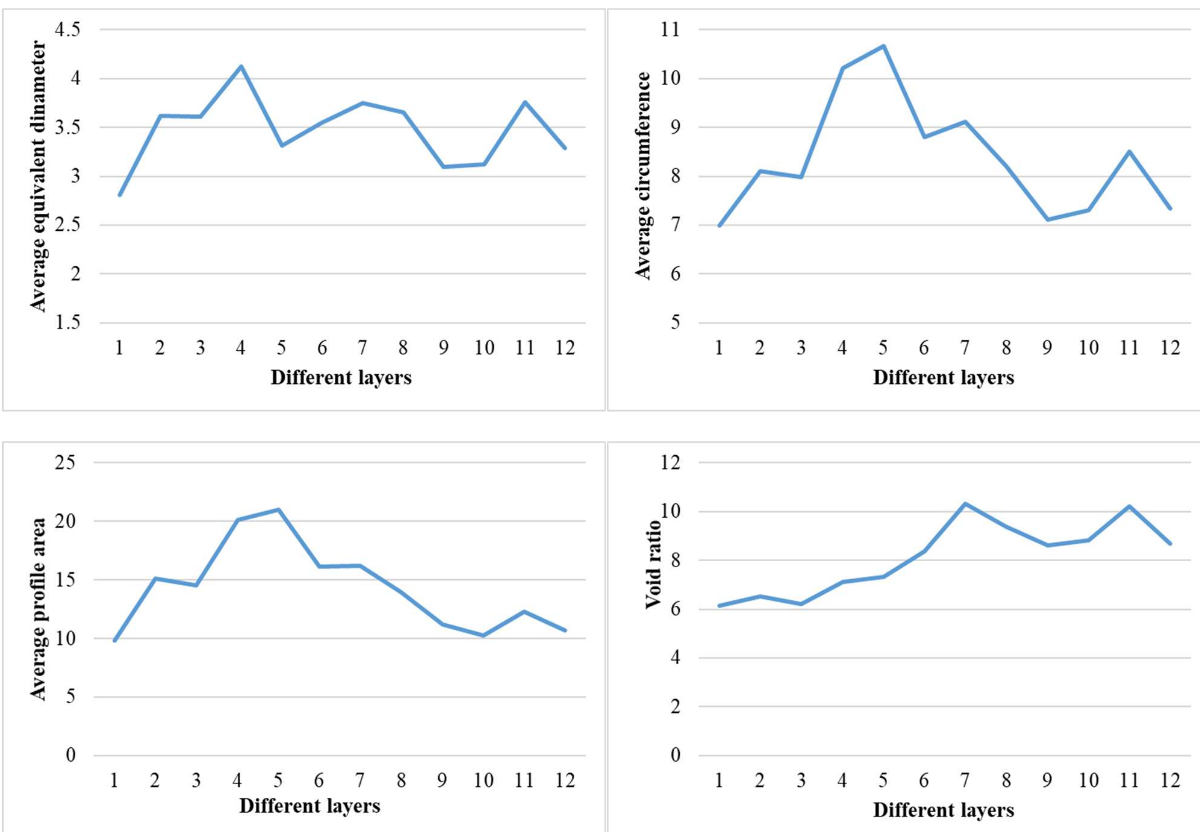

Fig. 9. Trend graph of indicators under different layers

According to Figure 9, as the layers are added, the average equivalent diameter, average perimeter and average contour area of the voids in each layer have roughly the same trend of change. Moreover, the trend change and porosity of these three index parameters are basically the same as the change trend of the layer, indicating that the index parameters are in line with the change trend of porosity. Combining with Table 3 and Figure 9, it can be seen that the change of porosity is about 8.14%, which is about 1.17% compared with the porosity of the selected construction asphalt mixture. This shows that the accuracy of the identification results of the porosity of the building asphalt mixture under the image processing technology is high.

5. Conclusion

In past studies, only macroscopic phenomena have been relied on to understand the performance of construction asphalt mixtures. The performance cognition of building asphalt mixture under this method is not only inaccurate, but also increases the research cost. The rise of image processing technology brings a new direction to the mesostructure research of building asphalt mixture. In this context, this paper mainly obtains the internal microscopic images of building asphalt mixtures through image processing technology, and then performs related processing work on the images. On this basis, a three-dimensional structural characteristic model of the void is constructed, and the model is experimentally analyzed. The result is expected. The main research work of this paper is divided into the following three points:

1) Research on construction asphalt mixture. This part mainly introduces the components of construction asphalt mixture. On this basis, the void structure of building asphalt mixture is selected as its meso-structure characteristic, and the measurement method of void ratio is systematically introduced from macroscopic and mesoscopic perspectives.

2) Image processing of construction asphalt mixture. This part mainly deals with the relevant technical processing work on the images of the selected building asphalt mixture. In the whole image processing process, one or more methods are compared and analyzed for each part of the image processing, and the appropriate method is selected for image processing.

3) Experimental analysis of void space structure model. In this part, after the relevant technical processing of the image of the building asphalt mixture, the void structure analysis model is constructed according to the processing results, and the sample of the building asphalt mixture is selected as the research object. The porosity detection based on the void structure analysis model was carried out, and the experimental results showed that the porosity detected by the model achieved the expected effect of the experiment.

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