Research on Intelligent Recognition Technology of Aggregate Parameters of Loose Asphalt Mixture Based on Image Processing Technology

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Abstract

Accurate acquisition of aggregate characteristics (shape, size and spatial position) is the basis for in-depth analysis of asphalt mixture grading, uniformity and surface texture. This paper proposes a modified recognition algorithm for loose asphalt mixtures based on digital image processing. The process first converts a True Color RGB image into a binary image during pre-processing. Then a Euclidean distance transform of the binary image is performed, which can be used to get the regional maximum value. In order to avoid over-segmentation caused by the traditional watershed algorithm, a modified watershed segmentation algorithm based on the extended-maxima transform is developed, effectively limiting the number of regional maximums to a reasonable range. Then the watershed ridge lines are superimposed on the original image. Hence, the aggregates are separated correctly, especially touching particles. Seventy images of untreated aggregates consisting of different particle sizes were tested. The results showed that the improved method could effectively segment the particles with accuracy as high as 98%. Finally, the proven methods are programmed and used to identify the particles of loose asphalt mixture. The results showed that the physical information of the loose asphalt mixture aggregates could be adequately recognized, and the accuracy is 96%, which is a solid foundation for the subsequent in-depth research.

1. Introduction

Asphalt pavement is widely used in the world, and the hot-mix asphalt (HMA) segregation is a common problem. There are three identified HMA segregations: gradation segregation, temperature segregation and aggregate-asphalt segregation. In this paper, the focus was on the gradation segregation, which was defined as the nonuniform distribution of coarse and fine aggregate materials in the finished HMA mat. Localized mat areas rich in coarse aggregate leaded high air voids and low asphalt contents; these conditions could cause the moisture damage, as well as the durability-related pavement distresses such as fatigue cracking, pothole formation, and ravelling. Conversely, mat areas rich in fine aggregate were associated with low air voids and high asphalt contents, making them susceptible to rutting and flushing. So, the morphological and spatial characteristics of aggregate played a key role in the properties of the asphalt mixture, and it was necessary to study the morphological and spatial characteristics through appropriate methods *[1,2].*

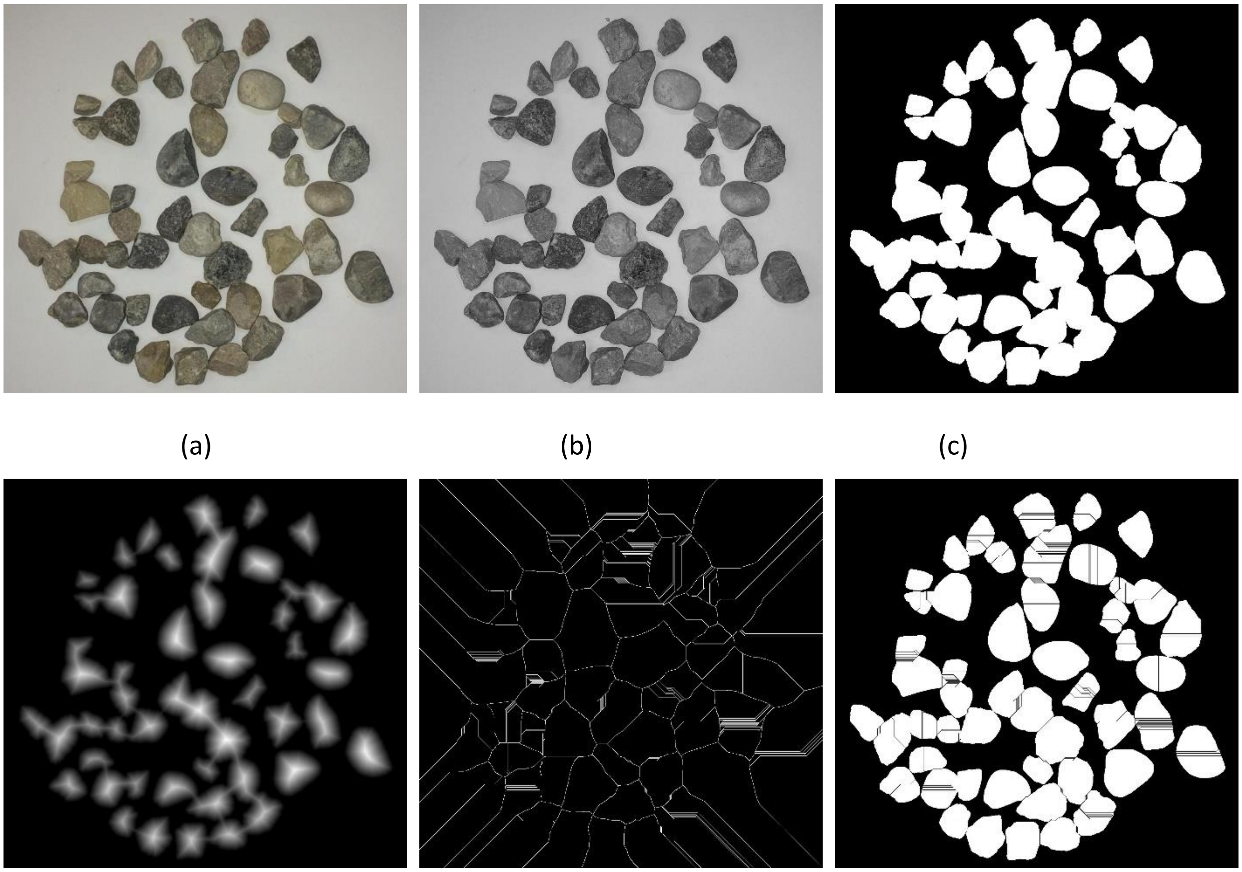
Numerous studies have been conducted to identify and mitigate its causes. With the development of computer technology, digital image processing (DIP) technique, which provided an objective and accurate measurement of aggregate particle size and shape properties in a rapid, reliable, and automated fashion when compared with traditional manual methods and tools, had been widely used as an advanced non-destructive testing method to investigate morphological properties of coarse aggregates *[3]*. Most of the researches are based on 2-Dimension (2D) or 3-Dimension(3D) images. Some experts quantified the aggregate form *[4-6]*, angularity *[7,8]* and texture *[9]* properties based on 2D images; furthermore, the 3D morphological properties of aggregates have been realized by X-ray Computed Tomography *[10-12].* However, most of these methods require particles to be artificially and uniformly spread out on a plane, and no touching particles exist; or, sliced samples which had been compacted and the particles is a good contrast with the dark background; or professional equipment like X-ray CT which means more cost. All the above reasons made most of these methods were difficulty in implementation in the field.

Recently, low-cost, high-resolution digital cameras have become available for daily use. A fast, simple, and cost-effective system which is composed of user-friendly hardware and software could be developed to facilitate quantifying of aggregate's morphological and spatial characteristics in project sites by commercially available digital cameras. The research aims at the rapid detection of the uniformity of the asphalt mixture during the paving process based on DIP technology. The ultimate goal is to achieve real-time detection the uniformity of mixture during the paving process. Before that, the problem of accurate identification of loose mixture has to be solved first. This paper mainly concerned how to efficiently and accurately identify and segment aggregates of loose asphalt mixture during the paving process, which was the solid foundation of uniformity analysis of loose asphalt mixture.

2 Image Segmentation

2.1 Watershed Segmentation Algorithm

Before Image segmentation, original RGB true color images which are taken by camera directly should be converted to grayscale intensity images firstly; afterward, resulting grayscale images are converted into binary images which all subsequent works are based on. These stages are very important, which can efficiently affect the results. During these processes, Filtering, Histogram Equalization and Morphological operations are used to improve the result of Binary image. Figure 1 (a), (b) and (c) separately shows the original RGB image, Grayscale image and Binary image. The binary image shows that the RGB image is exactly converted. Due to the needs of subsequent research, it is necessary to obtain the position and area information of each particle. While Figure 1 (c) shows that there are many particles touching each other, and this phenomenon is common in mixtures. Firstly, the particles in contact need to be accurately segmented.



(a) (b) (c)

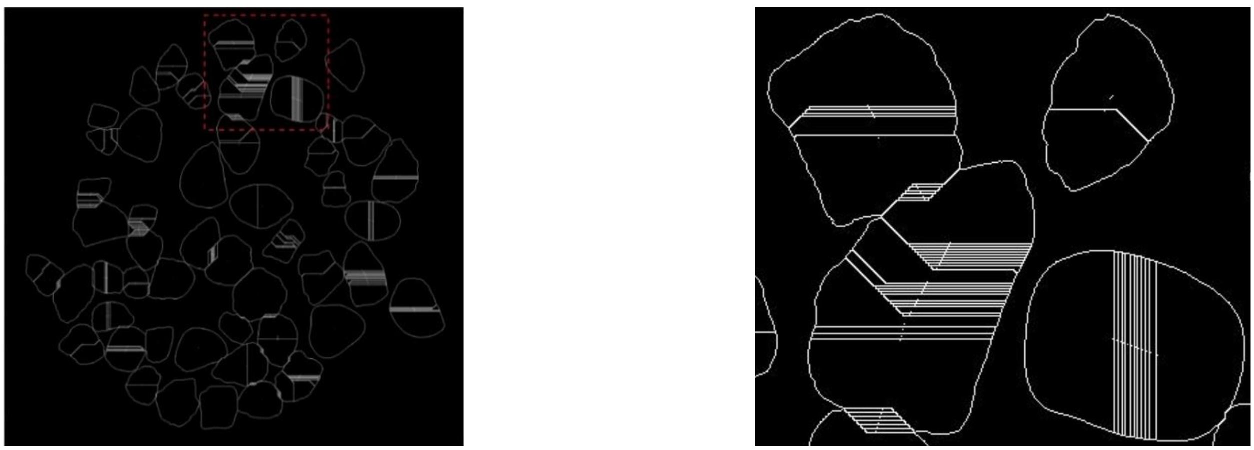
(d) (e) (f)

Figure 1 Watershed segmentation transform steps: (a) original RGB image, (b) grayscale image, (c) binary image, (d) distance-transformed image, (e) watershed ridgeline, (f) final result of watershed segmentation.

For easy display and understanding, take untreated aggregate particles with different sizes as an example. The image segmentation processing is shown in Figure 1. Image (a) represents the original RGB image taken by camera directly. Moreover, the image is converted to a grayscale image by forming a weighted sum of the R, G, and B components. The grayscale image is processed by filtering and histogram equalization for obtaining a high-quality result. After that, the image is binarized with a global threshold computed using Otsu's method, which chose the threshold to minimize the intraclass variance of the threshold black and white pixels and get the binary image (c). The result is subjected to a distance transform and get the grayscale image as shown in the image (d); afterward, the grayscale image is equivalent to a topological map, with maxima as peaks and minima as valleys. The watershed algorithm obtains the watershed ridgelines shown in the image (e); eventually, the segmentation image (f) is obtained by overlaying images (c) with the complement of image (e).

Comparing the image (c) and (f), we can find that many particles are seriously over-segmented. The main reason is that many particles have more than one regional maximum, just like showing in Figure 2.

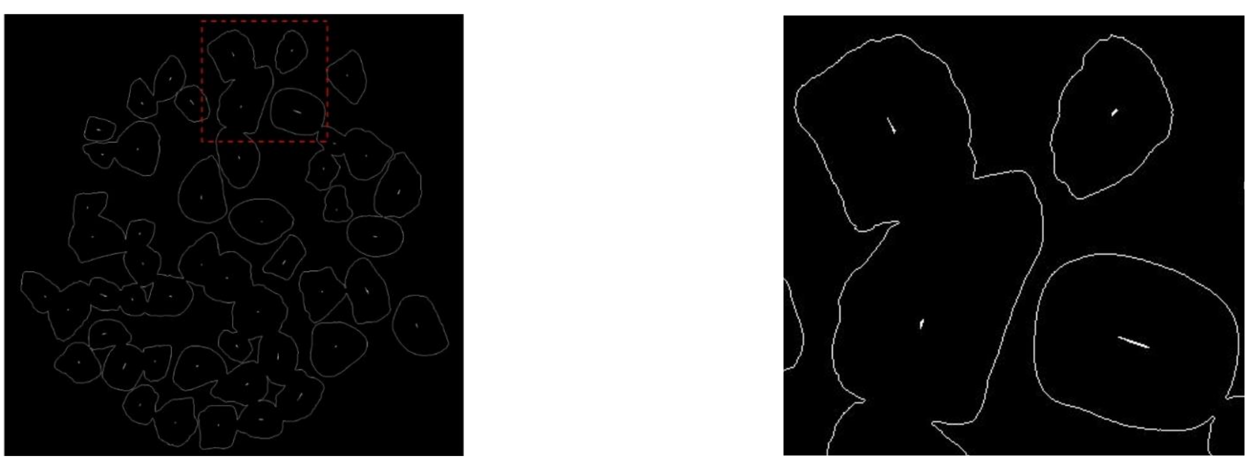
Figure 2 (a) shows the segmentation result directly using the watershed method, which contains the aggregate particles' contour along with the regional maxima and ridgeline. The regional maxima are obtained from the distance-transformed image in Figure 1(d). Figure 2 (b) is an enlarged region of the same image (marked by the red rectangle in Figure 2 (a)), which can clearly show multiple regional maxima on several aggregate particles. The result shows that directly using the watershed method will lead to the over-segmentation of particles, which will seriously affect the accuracy of particle identification or even lead to an error result. So, the first and most important problem is to divide touching particles into independent ones correctly.



(a) (b)

Figure 2 over-segmented result and regional maxima: (a) regional maxima with ridgeline and contour, (b) region enlarged image

Figure 2 shows that local maxima value leads to over-segmentation because each independent local maximum will be classified as a separate particle. Thus, the effective way to restrict the over-segmentation of particles is to reduce the number of regional maxima. The Extended-Maxima Transform (EMT) method can be used for this purpose. Its main idea is to change the independent regional maxima into one value for each particle by giving a suitable threshold. Before using the Watershed method, EMT is used firstly to optimize the number of regional maxima; subsequently, the Watershed method is used to segment the touching particles; eventually, accurate segmentation of particles can be achieved.



(a) (b)

Figure 3 Regional maxima by Extended-Maximum method: (a) regional maxima with contour, (b) region enlarged image

Figure 3 shows the optimized result of regional maxima by EMT. Figure 3 (a) shows the aggregate particles' contour along with the regional maxima. Moreover, Figure 3 (b) is an enlarged region of the same image, which can clearly show the aggregate particles' regional maxima. Comparing Figure 3 with Figure 2, we can see that, different from particles in Fig. 2, which contain a plurality of regional maxima, each particle in Fig. 3 contains only one corresponding region maximum value optimized by EMT. Optimized Watershed method based on EMT can obtain accurate segmentation result of particles.

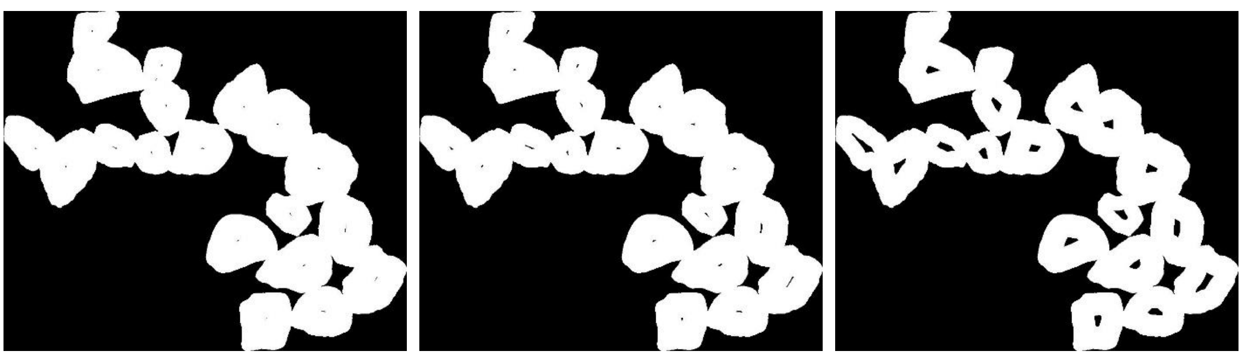
2.2 Watershed Segmentation Algorithm Based on the Extended-Maxima Transform

Image segmentation is a crucial step from image processing to image analysis. The segmented digital image is divided into many disjoint areas, including the foreground (interested target region) and the background (the irrelevant information). The effect of image segmentation has an essential impact on the subsequent analysis and calculation.

In this paper, a Watershed algorithm based on EMT is proposed, which can expand and merge multiple maxima points inside the particles and make sure that the regional maximum point of the particle exists uniquely. This algorithm can significantly eliminate the over-segmentation, and segment particles fast and accurately, especially for touching particles.

2.2.1 Determination of the Optimal Threshold

EMT method is based on H-Maxima transform. Intuitively, the maximum value of the original grayscale image is M, and the threshold is h. H-Maximum transformation means that all the intensity value which are larger than h will convert into $M-h$, and others, convert into 0. The transformed image is still a grayscale image; while, Extended Maximum Value transformation will convert all the intensity values which are higher h into 1, and others convert to 0, so the transformed image is a binary image.



(a) (b) (c)

Figure 4 Regional maxima result with different threshold h: (a) $h = 0.01$, (b) $h = 0.02$, (c) $h = 0.05$

Figure 4 shows the different results of regional maxima with different threshold h. The dark areas of the central part of particles are the regional maxima region under different h, and white parts are particles. When h is too small, $h = 0.01$, the number of regional maxima is more than the actual number of particles. And the particles were over-segmented. While when h is too large, $h = 0.05$, the number of regional maxima is less than the actual number of particles. In this case, particles were insufficiently segmented. When h takes an appropriate value, $h = 0.02$, the number of regional maxima is equal to that of particles, and the particles were correctly segmented.

By analyzing Figure 4, the key to EMT algorithm is how to determine the optimal threshold value, h, which decides whether the correct segmentation of particles can be achieved. As known, when particles are correctly segmented, the number of particles will be equal to that of regional maxima. Based on this, the optimal threshold value, h, can be determined. Firstly, the binary image is processed by Euclidean distance transformation to obtain the grayscale image; afterward, choosing an initial threshold value h_0, usually taking a small value at the beginning and here $h_0 = 0.001$, and then perform EMT method on the obtained grayscale image; subsequently, increasing h_0 by an increment Δh and repeat the procedure until getting the optimum value of h. The optimal value of h is determined by comparing the relationship between the number of regional maxima, N_1, in the binary image obtained by EMT and the number of particles, N_2, after the watershed segmentation based on EMT. When an allowable range of the threshold parameter h is decreased, particles can be separated. Experimental data show that it can accurately predict the number of particles when a small enough threshold h is selected. Figure 5 shows the relationship between h and N_1 and N_2: The data represent a stepwise change of N_1 and N_2 with the increase of h. When h is in a certain interval, [0.08-0.14], N_1 is always equal to N_2. And both N_1 and N_2 decrease when h increases. The optimized segmentation threshold value is obtained in the threshold range. The correct segmentation result (N_1=N_2=50) can be obtained in the range [0.016, 0.043].

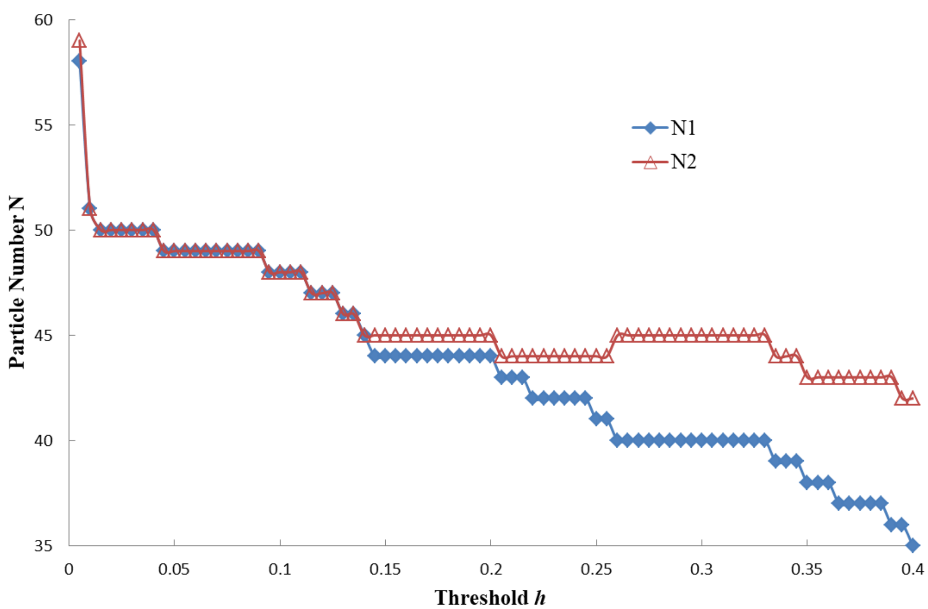


Figure 5 Curves of N1 and N2

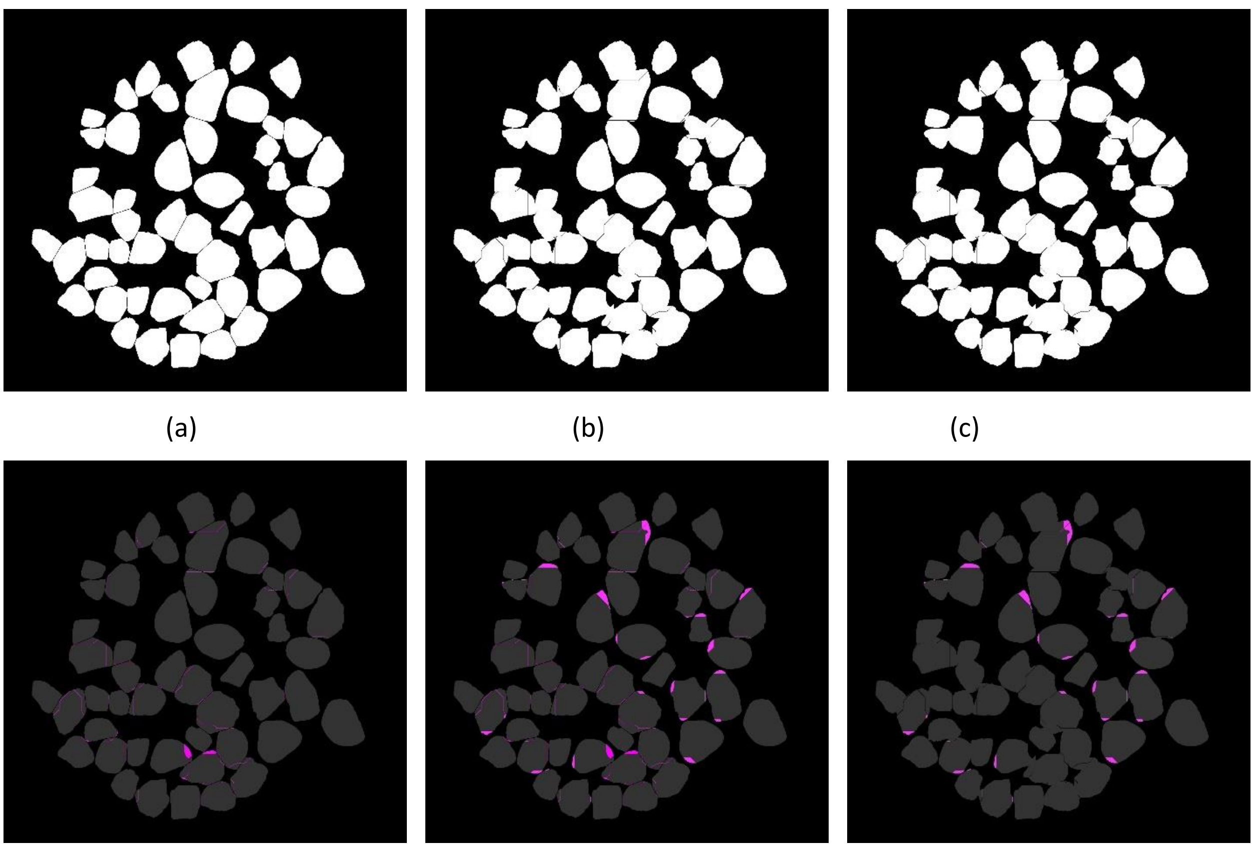
(a) (b) (c)

Figure 6 Segregation Results: (a) correct-segmentation, (b) over-segmentation, (c) insufficient-segmentation

Figure 6 shows the effect of different h value on the segmentation results. Figure 6 (b) is the segmentation result when h equals to 0.01, and over-segmentation occurs with the result N1=N2=51 which is more than the actual number; Figure 6 (c) shows the insufficient-segmentation result when h=0.1, and the segmentation result is N1=N1=48 which is less than the actual number.

By analyzing Figure 6 (b) and (c), we conclude that the value of h has a great influence on the segmentation effect. When h is relatively small, as shown in Figure 6 (b), the particle, marked by the red circle, was wrongly divided into two, resulting the identification result is greater than the actual number of particles. However, when h is too large, Figure 6 (b) shows that the touching particles cannot be effectively segmented and the particles, marked by the red circle, were wrongly identified as one particle. The number of particles obtained by this process is less than the actual number. Figure 6 (a) shows the correct-segmentation when h equal 0.02. We can see that touching particles can be correctly identified and segmented, and the identification number is equal to the actual number of particles. Furthermore, the area of the regional maxima is increase as h increases. The change in the area of regional maxima is the cause of the difference in the number of identifications. We can always find a suitable h to segment the particles correctly, and the area of regional maxima will also be in a reasonable range.

2.2.2 Effect of Segmentation Method



(a) (b) (c)

(d) (e) (f)

Figure 7 Effect of segmentation methods: (a) Manual segmentation based on corner points, (b) Partial segmentation based on EMT, (c) Global segmentation based on EMT, (d) composite of Manual

segmentation and Partial segmentation, (e) composite of Manual segmentation and Global segmentation, (f) composite of Partial segmentation and Global segmentation

Analyzing the results of segmentation, we found that different segmentation methods would lead to different results. Figure 7 (a) to (c) shows the different results obtained by different segmentation methods. Image (a) is the result of Manual segmentation method based on corner points which can accurately divide the touching particles, but it is time-consuming. So, when the number of particles is large, this method is no longer applicable. Image (b) is the result of Partial segmentation method based on EMT. In this method, firstly, the parts that are not connected are identified, and then the improved watershed method based on EMT is used to segment the touched particles of each part. Image (c) is the result of Global segmentation method based on EMT. Different from the Partial segmentation method, Global segmentation method is used to segment the whole particles directly.

Figure 7 (d) to (f) shows the differences, which is colored by purple, of different segmentation methods. Image (d) shows the difference between Manual segmentation and Partial segmentation methods. The marked purple area was deleted in Partial segmentation method. Similarly, Image (e) and image (f) separately show the differences between Manual and Global segmentation methods and that of Partial and Global segmentation methods. Although all the three methods can obtain the correct number of particles, there are still significant differences: Manual segmentation based on corner points can get the accurate shape information of particles, and there is no loss of any area; Partial segmentation method based on EMT can obtain acceptable shape information of particles with smaller area loss while Global segmentation method obtains the result with a large area loss, and the shape of some particles is obviously changed. As a result, Partial segmentation method will be a good choice when considering time consumption and accuracy.

2.3 Optimal Threshold Determination and Verification

In order to obtain the optimized segmentation threshold value h , by analyzing Figure 5 and Figure 6, we found that N_1 and N_2 had to satisfy two conditions: the first one is $N_1 = N_2$. When N_1 equals N_2, the approximate range of h can be obtained. Another condition is the cumulative quantity, N, when both N_1 and N_2 are equal to a certain value. This value is a statistical result, obtained by statistical analysis of a large number of results. By N, we can further narrow the range of h and obtain the optimal threshold. The selection criterion of h is when N_1 is equal to N_2 and the cumulative quantity N is greater than or equal to 5 with the step length of 0.001. Because there are multiple values satisfying this requirement, the first one that satisfies the requirement is selected as the threshold.

Seventy images which are content different size and number of particles were used to test the segmentation accuracy of the improved watershed method based on EMT. All samples can be firstly divided into two categories: one is that particles are with the same size in one sample while different particle sizes between different samples, which can be called single-size sample; another one is the sample with different size of particles, which can be called mixture sample. Furthermore, the single-size sample can be further divided into five categories according to the size of the particle size, which particles size is 4.75mm – 6.5mm, 6.5mm – 9.5mm, 9.5mm – 12.5mm, 12.5mm – 13.5mm and 13.5mm – 16mm respectively. The mixture samples can be further divided into two categories: one is named fine mixture sample in which the minimum particle size is 4.75mm, and another one is named coarse mixture sample in which the minimum particle size is 6.5mm.

The segmentation results are shown in Figure 8. The results show that the average segmentation accuracy rate of each sample is greater than or equal to 98%, and the minimum value of accuracy is 92%. When the size of the particle is small like less than 6.5mm, the results of the identification number is less than the actual number. While, when the minimum size of the particle is greater than or equal to 6.5mm, the identification results are greater than or equal to the actual value. The main reason is that when a large number of smaller particles are in contact, multiple touching particles are easily mistakenly treated as a single particle, resulting in a smaller number of identifications than the actual number; on the contrary, when the particle size is big enough like 6.5mm, touching particles can be correctly segmented but single particle is easily over-segmented which results in a greater number of identifications than the actual number.

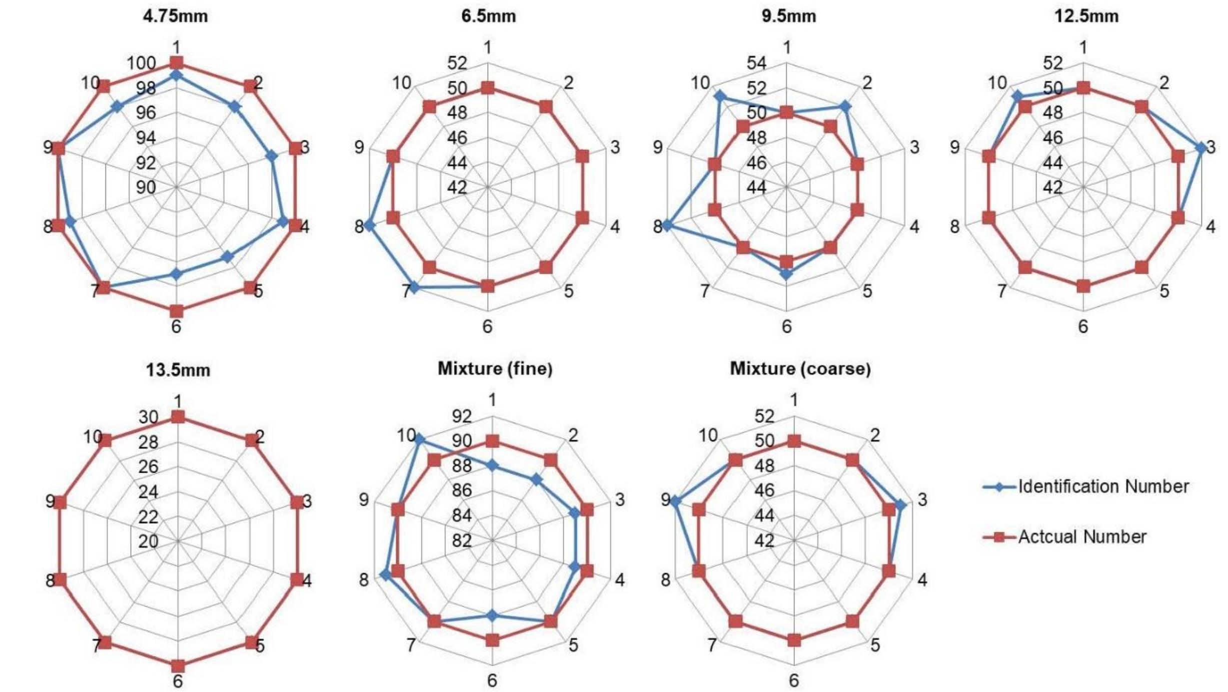
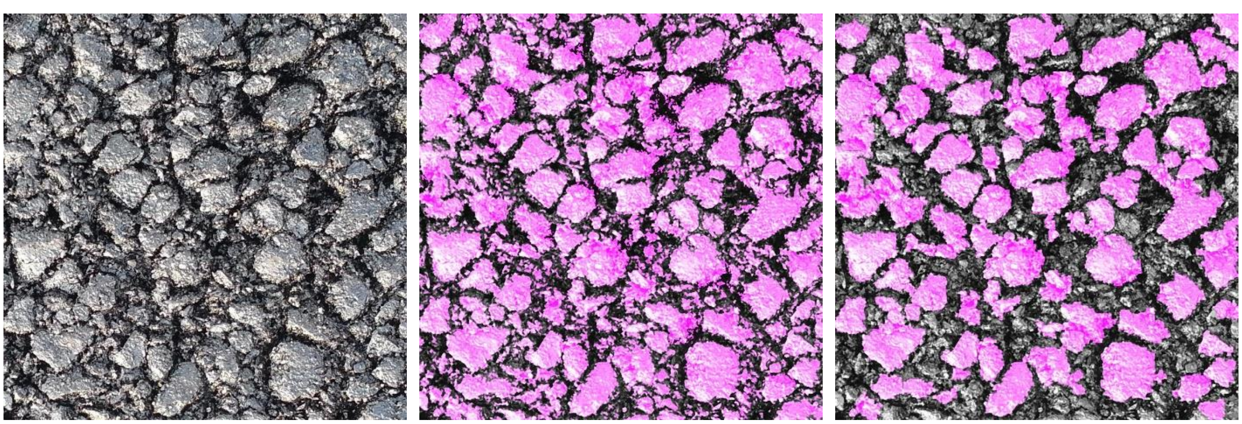
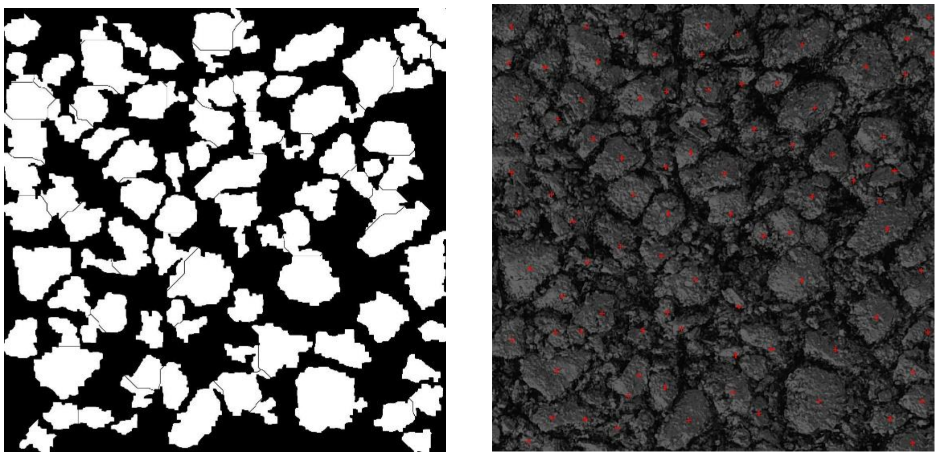


Figure 8 Segmentation results

As the particle size increases, the identification accuracy of which either single-size samples or mixture samples generally increases gradually, but there are also regional fluctuations. For instance, the identification accuracy of samples with the size between 9.5mm and 12.5mm has large fluctuations. The shape and number of contact particles are the main factors leading to recognition errors. The more the strips of particles and the number of contact particles, the easier the particles are to be segmented. However, the recognition accuracy is still acceptable.



(a) (b) (c)



(d) (e)

Figure 9. Watershed Segmentation Results of Loose Asphalt Mixture based on EMT: (a) Original asphalt mixture, (b) Composite image with whole identified particles, (c) Composite image with identified particles larger than 4.75mm, (d) Segmentation result of identified particles larger than 4.74mm, (e) Marked grayscale image

Although the improved watershed method based on EMT is shown with unbound particles, it is also applicable to identify the particles of loose asphalt mixture (LAM). Figure 9 shows the identification and segmentation results of LAM with the watershed method based on EMT. Image (a) shows the original RGB image of LAM mixture taken from the field site. Image (b) is a composite image of the grayscale image and all identified particles image; the image shows that identified particles are in good agreement with the actual situation. In order to suppress the adverse effect of small particles on the segmentation result, particles less than or equal to 4.75 mm are removed, the result is shown in image (c); subsequently, the identified particles larger than 4.75mm are processed by the watershed method based on EMT, and the segmentation results are shown in image (d). Unlike smooth edges of unbound particles, edges of identified LAM particles are jagged, mainly due to the presence of bitumen causing the particles' boundaries to become blurred. Image (e) is a marked grayscale image, in which the centroids of identified particles are marked by red star symbols. Although the number and shape of the identified particles cannot be exactly consistent with the actual situation, they still maintain good consistency and can be used for the subsequent analysis and research. By comparing the particles' number results of manual recognition method with that of the watershed method based on EMT, the correct rate is still as high as 96% and more.

3. Conclusion

From the previous theoretical analysis and experimental results, particles with irregular shapes and sizes, particularly those touching particles, are usually over-segmented by the traditional watershed segmentation algorithm, which has an adverse effect to the subsequent image processing. This paper proposed an improved watershed segmentation method to obtain more accurate morphological and spatial information.

1) Developed an improved watershed method based on EMT, which achieved accurate segmentation of aggregates, especially the contacted particles; unlike the traditional method, the developed watershed method effectively suppressed over-segmentation and insufficient-segmentation.

2) Different segmentation methods are compared. Manual segmentation method based on corner points obtained the most accurate results while it was time-consuming and labour-consuming.

Compared with Global segmentation method, Partial segmentation method greatly reduced the loss of particle area without increasing excessive time consumption.

3) Experimental data show that, within the optimal range of the threshold value, touching particles can be effectively segmented by the proposed algorithm, and the correct number of particles can be obtained. The accuracy of segmentation is as high as 98% and 96% separately to untreated aggregates and loose asphalt mixture.

Further Study:

1) Consider the influence of different asphalt mixture types on recognition accuracy. How to objectively verify the correctness of asphalt mixture identification instead of visual verification method needs to be studied in the future.
2) Develop the field collection system. Moreover, the impact of shooting conditions (such as shooting height, illumination, mechanical vibration and Vehicle speed) on the particle recognition need to be considered.
3) Develop the uniformity algorithm based on the identification results.

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