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Image processing of coarse and fine aggregate images

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For coarse and fine aggregate, and SEM cross section images, an automatic textured image segmentation method, and an automatic measuring scheme, are described respectively here. The satisfactory results show that the method proposed here would be very useful for the development of an automated quality control system for use in an industrial environment.

1. Introduction

The construction industry in the UK currently uses in excess of 218 million tones of crushed aggregate per year. The quality of the aggregate produced in terms of the consistency of its size and shape also has a major influence on the quality (particularly in relation to workability and durability) of the concrete and blacktop mixes subsequently produced. In this paper, by using images processing technique, we aim at the automatic measuring of size and shape of coarse aggregate, and unsupervised segmentation of fine aggregate images and SEM (Scanning Electron Micro-scale)images.

In this work, with fine-grained aggregates (particles $< 75\,\mu$m) and SEM cross section images, we mainly focus on unsupervised textured image segmentation techniques. The goal is to find the boundaries between the different textured regions. Since the texture provides important characteristics for surface characterization and object identification, texture features of aggregate mixes were obtained first by using wavelet-based measurement. The features used are believed to be among the most meaningful features for texture image characterization. Following this, an automatic segmentation method was developed. With coarse aggregate objects, an image processing technique was then used to separate the individual particles before applying measurement techniques. By using morphological image processing as an analyzing method, we are able to measure the size and shape characteristics of an aggregate or mix of aggregate. This can enable us to make the most efficient use to be made of the aggregate and binder.

2. Fine-aggregates and SEM textured image segmentation

With textured images such as fine aggregate and SEM images, based on the wavelet transform, the characters of observed texture image are extracted. Energy feature vectors are created over the wavelet transform coefficient field. Once the texture feature set associated with a texture image is completed built, the following task is to map the texture features of the observed image into its corresponding class labels over the feature space. During this procedure, the segmentation algorithm combined with Mixture Gaussian Modeling and a simulated annealing technique was developed. By means of taking account of the knowledge of the local area in the Gaussian mixture model, the improved textured image segmentation results are obtained.

2.1. Texture analysis and textured image features

We use a wavelet multi-resolution transform attractive properties, by carrying out a wavelet transform on the observed image, and successively decomposing the lowest sub-band at each level, a pyramid tree structure is obtained which provides the details of different resolutions from finer toward the coarse. The output of filter banks can provide full coverage of the frequency spectrum. With $J = 3$ level wavelet transform, it can be decomposed into $3J + 1$ sub-band channels:

$$C(\text{Channels}) = \left\{\mathrm{LL}_J, \mathrm{LH}_J, \mathrm{HL}_J, \mathrm{HH}_J, \ldots\ldots, \mathrm{LH}_1, \mathrm{HL}_1, \mathrm{HH}_1\right\}.$$

This results in 10 main wavelet channels. The energies of the 10 channels related with the wavelet transform of the local area are used as features for the segmentation in the textured areas of the image. This reflects the distribution of energy along the frequency axis over scale and orientation. The energy of each channel is calculated by the equation:

$$E_c = \frac{1}{PQ}\sum_p \sum_q \left|w_{pq(c)}\right|, \tag{2.1}$$

where $c = 1, 2, 3, \ldots, 3J + 1$, $J = 3$ here and P, Q are wavelet coefficients size in channel c.

The feature vector $Fs(i,j)$ is

$$Fs_{(i,j)} = \{E_c(\mathrm{LL}_3), E_c(\mathrm{LH}_3), E_c(\mathrm{HL}_3), E_c(\mathrm{HH}_3), E_c(\mathrm{LH}_2), E_c(\mathrm{HL}_2), E_c(\mathrm{HH}_2), E_c(\mathrm{LH}_1), E_c(\mathrm{HL}_1), E_c(\mathrm{HH}_1)\}. \quad (2.2)$$

2.2. Unsupervised segmentation combined with simulated annealing and local knowledge

The segmentation procedure in the feature space is the process of clustering it. The aim is to find homogenous clusters of feature vectors appearing as similar properties in the feature space and to label each cluster as a different region. On one side, with the high multi-dimensional feature space, this multi-dimension automatic clustering task becomes much tougher and it belongs to a kind of non-convex optimization problem. On another side, for each pixel considered, the texture vector of it not only should in some

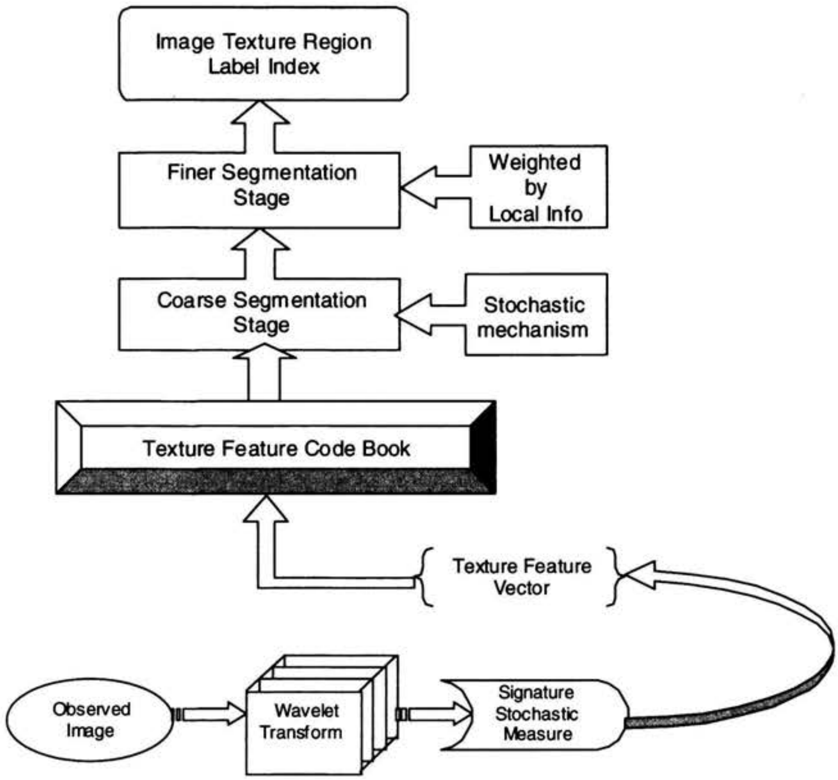

FIGURE 1. The flow chart for automatic segmentation.

way capture the properties of its local region around the pixel, but also in fact the neighboring pixel should have preferably the same label index. However, for the general mixture Gaussian clustering method, in the E-step, the knowledge of local area pixels is not included, this will lead to ruggedness segmentation result. In the M-step or decision phase, the algorithm adopts the hard-decision mapping based on the extracted probability, and this will cause the iteration algorithm to become stuck in a local optimum point as well.

In order to overcome these two drawbacks, we propose a method which introduces a weighted mixture model by combining the local knowledge, and meanwhile, simulated annealing strategy was used during the model optimization procedure. The work frame for automatic segmentation of fine-aggregate and SEM images is described in Fig. 1.

In the coarse segmentation stage, for Gaussian model k, we built the probability equation regarding to feature vector Fs as:

$$P\Big(Fs \,|\, \text{Center\_}Fs(k), {\textstyle\sum_k^{-1}}, t\Big) = \frac{1}{Z(t)} \exp\Big[-\frac{1}{2T(t)}\big(Fs - \text{Center\_}Fs(k)\big)^T {\textstyle\sum_k^{-1}} \big(Fs - \text{Center\_}Fs(k)\big)\Big], \quad (2.3)$$

where $k = 1, 2, \ldots, K$, and

$$\textstyle\sum_k = \frac{1}{K}\sum \big(Fs(i,j) - \text{Center\_}Fs(k)\big)^T \big(Fs(i,j) - \text{Center\_}Fs(k)\big),$$

$$Z(t) = \sum_{k=1}^{K} \exp\Big[-\frac{1}{2T(t)}\big(Fs - \text{Center\_}Fs(k)\big)^T \cdot {\textstyle\sum_k^{-1}} \big(Fs - \text{Center\_}Fs(k)\big)\Big].$$

The simulated anneal temperature scheme $T(t)$ is used, $T(t) = \frac{1}{T_0(t-t_0)}$. T_0 and t_0 are constants, and t is associated with the iteration counter during the optimal process. In the fine segmentation stage, for a textured image, every texture region has to extend over a significant area. This means isolated labels and very small regions are disregarded in segmentation. From this point of view, we believe the texture region should often be large enough area for each kind of texture, we build a weighted mixture Gaussian model with second order neighbourhood as follows

$$P(Fs \,|\, \theta) = \sum_{k=1}^{K} \frac{1}{Z} \alpha_k P_k \exp\Big[-\frac{1}{2}\big(Fs - \text{Mean\_}Fs(k)\big)^T \cdot {\textstyle\sum_k^{-1}} \big(Fs - \text{Mean\_}Fs(k)\big)\Big]. \quad (2.4)$$

The parameters set is

$$\theta = \left\{ \alpha_k, P_k, \text{Mean\_}Fs(k), \sum\nolimits_k \right\}_{k=1}^{K},$$

where $P_k = 1/K$, $\alpha_k > 0$, and $\sum \alpha_k = 1$ $(k = 1, 2, \ldots, K)$. α_k is the weighting parameter which is associated with the label index, providing knowledge of the current local area.

3. Image processing for coarse aggregate measuring

In the coarse aggregate measuring procedure, in order to correctly address object properties appearing in the observed image, successful segmentation is a crucial step. Since the appearance of objects and background are quite similar to each other, image enhancement, image edge detection and image filtering techniques are very necessary. Once the stone objects are successfully segmented from their background, they were labelled.

For each individual object, the object characters (such as: stone object area, stone object diameter, stone object major length and stone object minor length) were calculated by using a morphological image processing method. The overall flow chart for image processing of coarse aggregate is shown in Fig. 2.

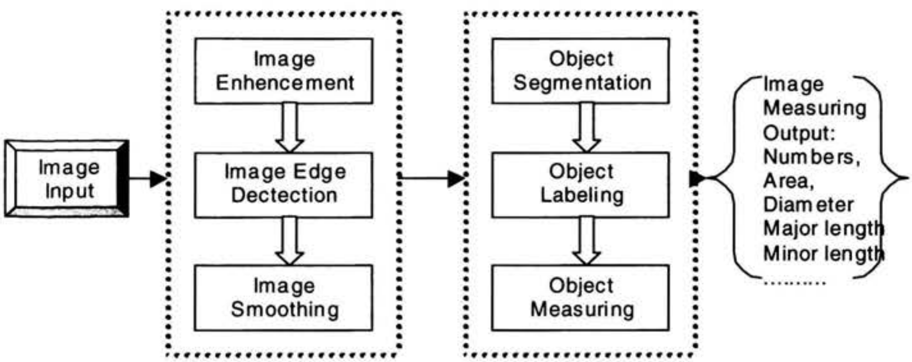

FIGURE 2. The flow chart for automatic measuring.

4. Experiment Results

The experiment results of image processing of coarse and fine aggregate and SEM cross section images are given here. With fine aggregate, the sand passing 600 μm image, the sand passing 300 μm image and the sand passing 75 μm image were regular cut and composed together as shown in Fig. 3(a). The automatic texture segmentation result was given in Fig. 3(b). By applying the unsupervised textured image segmentation method on it, three kinds of sand were correctly classified into three region labels. For SEM cross section image processing, the original image was shown in Fig. 4(a). The results of automatic segmentation in coarse stage and fine stage were shown in Fig. 4(b) and Fig. 4(c) respectively.

(a) (b)

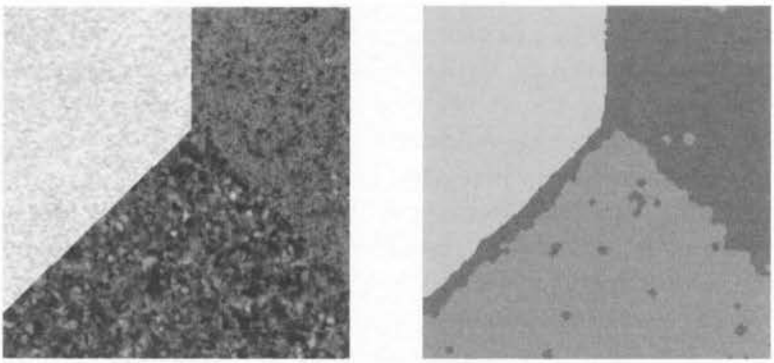

FIGURE 3.

(a) (b) (c)

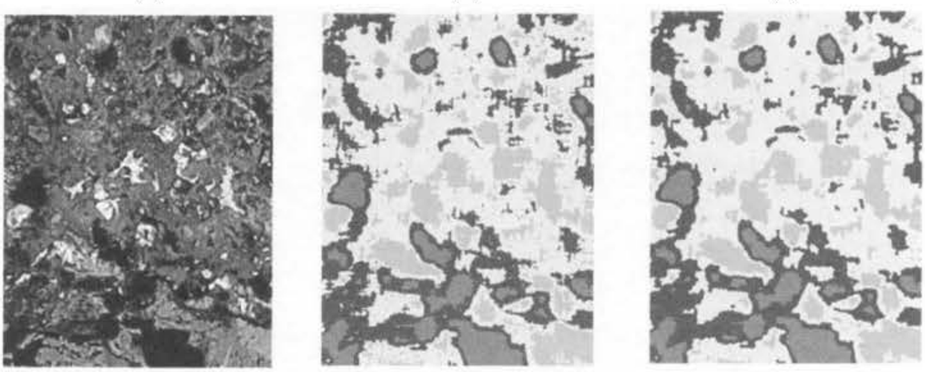

FIGURE 4.

Figure 5(a) is the original coarse aggregate image. After applying segmentation on coarse aggregate, its corresponding object labelling image is shown in Fig. 5(b). The colour of objects related to the object order. The properties

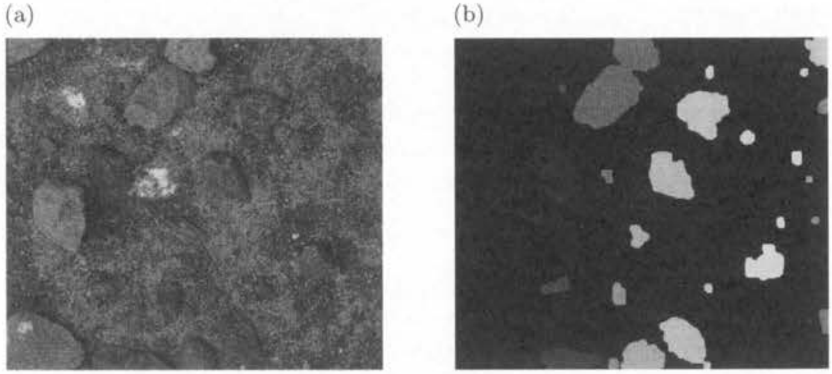

FIGURE 5.

such as the area, major-axis, minor-axis and diameter are shown in Fig. 6. According to object area feature, the objects were clustered in 10 bins. The number of objects in each bin is shown in Fig. 6 as well.

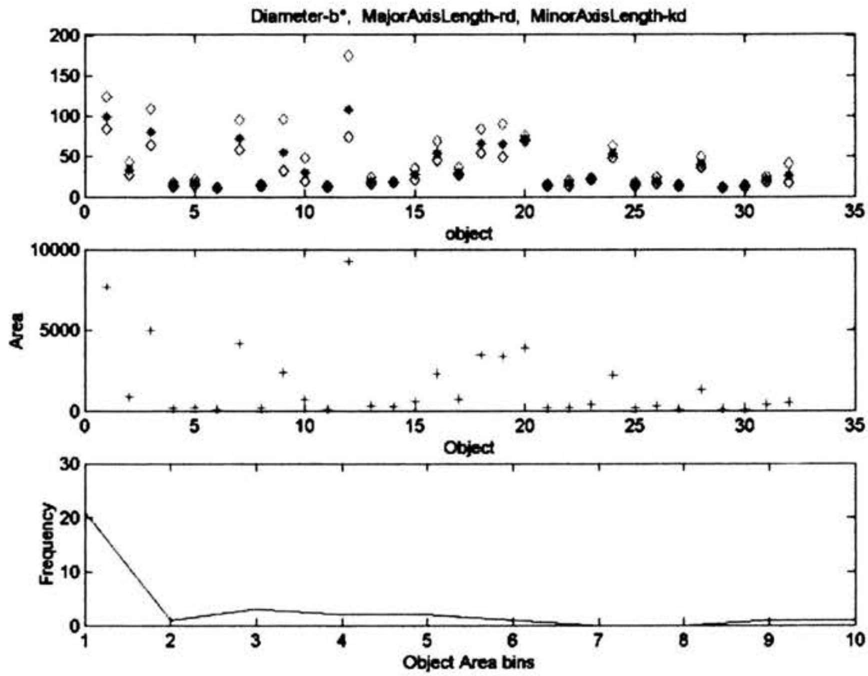

FIGURE 6. The properties of objects.

5. Conclusion

By using proposed unsupervised image segmentation and morphological image processing, very satisfactory results for automatic texture image segmentation and coarse aggregate measuring were obtained. This work will lead towards the development of an automated quality control system for use in an industrial environment.

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