Edge Affine Invariant Moment for Texture Image Feature Extraction

Yiwen Dou(✉), Jun Wang, Jun Qiang, and Ganyi Tang

College of Information and Computing Sciences, Anhui Polytechnic University, Wuhu 241000, Anhui, People's Republic of China
yiwend@sina.com

Abstract. Texture image feature extraction is one of hot topics of texture image recognition in recent years. As to this, a novel technique for texture image feature extraction based on edge affine invariant moment is presented in this paper. Firstly, each texture image is checked by a short step affine transformation Sobel algorithm initially. Then, the corresponding texture image feature named edge affine invariant moment will be calculated and added to feature vector set. Subsequently, cluster analysis will be loaded upon the set by K-means algorithm and the categorized texture image can be obtained. Three simulation experiments closed to real environment over the two well-known Brodatz and KTH-TIPS texture databases are performed in order to test the efficiency of our proposed algorithm.

Keywords: EAIM (edge affine invariant moment) · Feature extraction · K-means · SSAT (short step affine transformation Sobel)

1 Introduction

Image texture analysis is a hot issue in many fields such as computer vision [1], image retrieval [2], image processing [3] and machine vision [4] etc. Its ambiguous definitions lead to non-unified framework structure for image texture analysis till now. In spite of different research contents about texture image segmentation [5], classification [6], synthesis [7], retrieval [8] and restoration [9] etc., its essential work is to extract texture features [10]. At present, the main goal of texture feature extraction is good robustness and high computational efficiency.

The typical method of texture feature extraction includes two major categories. One is based on point feature and another based on gray feature. The feature vector of SIFT or SURF is extracted from the texture feature based on the feature extraction. Because SIFT is not a global feature descriptor, Yong Xu et al. [11] proposed a multi-fractal spectrum method which can extract the global feature descriptor of texture images. This SIFT-like descriptor had been applied to both static and dynamic textures and resulted in good extraction performance. Jayaraman et al. [12] used SURF to obtain the iris texture features, and these features will be used to classify initial iris color feature data. The method ultimately improves the accuracy of iris recognition. Those feature extractions based on point feature can obtain too much point features and

F. Chen and Y. Luo (Eds.): Industrial IoT 2017, LNICST 202, pp. 83–90, 2017.
DOI: 10.1007/978-3-319-60753-5_9

are easily disturbed by many kinds of noise. Obviously, they fail to meet the practical application requirements of texture feature extraction.

Siqueira et al. [13] used Gaussian multi-scale expression and image pyramid to extend the gray level co-occurrence matrix so as to obtain multi-scale texture feature. They applied their algorithm to five benchmark texture data sets and got a good recognition effects. However, in the calculation of the gray level co-occurrence matrix, it is necessary to calculate the probability of the co-occurrence of the pixels in the distances and directions and it also needs to calculate more texture features. So the drawbacks of texture feature extraction based on gray feature become more and more prominent.

In recent years, the research based on line features, especially on the edge feature is more state-of-the-art. Compared with point and surface features, line features can not only reduce noise interference factors but also improve calculation efficiency.

In this paper, we propose a feature extraction method based on edge affine invariant moments (EAIM) for texture image feature extraction. The edge image is obtained by short step affine transformation Sobel algorithm (SSAT [14]) and then its edge affine invariant moment will be calculated to build feature vectors. Finally, the K-means algorithm [15] is used to classify texture images in feature vectors space.

The rest of this paper is organized as follows. In Sect. 2, we briefly introduce some related work about texture image feature extraction methods and SSAT. The detailed derivation process of the proposed EAIM is described in Sect. 3. In Sect. 4, experiment results are analyzed and discussed. Finally, conclusions and further research are addressed in last section.

2 Related Work

2.1 Short Step Affine Transformation Sobel

Usually in complex environment, images will be enormously affected by light changing. At that time, we cannot get good edge information because of low illumination. In [14],

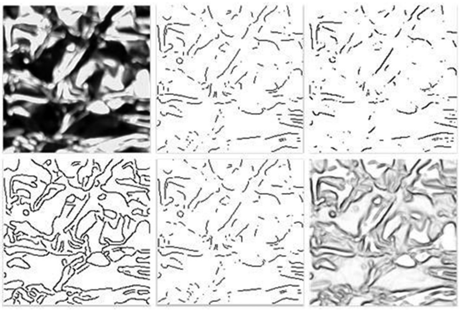

Fig. 1. Edge images obtained by different edge extraction methods (The first row shows the original image, Prewitt and Roberts segmentation effects, respectively. The second row shows canny, sobel and SSAT segmentation effect, respectively.)

the authors proposed SSAT method which is used affine invariance to extract image edge directly. In order to reduce the influence of light interference, we will use this edge extraction algorithm to promote the real-time ability of our scheme.

As can be seen from Fig. 1, Canny operator preserves the best details of the edge image and the distinction between the target and the background is also shown better than the others. SSAT algorithm outperform the Prewitt, Roberts and Sobel operator because its mechanism.

2.2 Sift and Surf

SIFT descriptors [16] are obtained by using difference of Gaussian (DoG) and gradient histogram based on 128-dimensional vector. The application of this feature description to object classification is the classic strategy of pattern recognition. SURF local feature description [17] is built on the SIFT algorithm. SURF's box filter obtains multi-scale pyramid images by convoluting the original image and performs fast Hessian matrix approximation in the integral image. These strategies make SURF obtaining faster feature points calculation.

However, as to complicated and overloaded texture image, more feature points mean the algorithm will spend more time to calculate and it results in wasting the recognition efficiency. So SIFT and SURF are all less used to extract the texture features in real.

From Fig. 2, we can see that texture feature extraction using feature points can not carry out accurate texture image description which will greatly affect the effect of classification recognition.

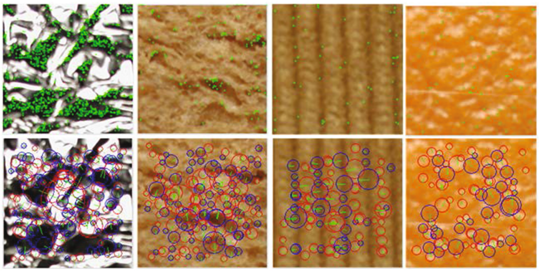

Fig. 2. SIFT and SURF feature extraction of texture images (The first and the second row are SIFT and SURF feature extraction respectively.)

2.3 Gray Level Co-occurrence Matrices

GLMC [18] is used as a statistical method to describe the image texture information method. First, the matrix is constructed according to the direction and distance between those image pixels, and then the meaningful statistical features are extracted from the matrix to describe the texture. Because the texture is the adjacent pixel or the adjacent region on the grayscale geometric position of the relationship between the characterizations or the statistics in the same position of the relationship between a pair of gray-scale pixel correlation, you can use some conditional probability of this pair of pixels to describe its texture characteristics. However, because of the huge computational complexity, it is not the first choice in real-time systems.

The process of extracting texture features is introduced briefly. In the following we will give a series of mathematical description and a set of edge affine invariant moments.

3 Edge Affine Invariant Moment

3.1 Edge Moment

The basic definition of the $(p + q)$th continuous edge moments [19] in 2D is given below:

$$e_{pq} = \int_L x^p y^q ds \tag{1}$$

where L is the edge curve of closet region Ω, $p, q = 0, 1, 2, \cdots$, $ds = \sqrt{(dx)^2 + (dy)^2}$.

3.2 Edge Affine Invariant Moment

In practical applications, we define the edge center moment as follows:

$$\mu_{pq} = \int_L (x - \overline{x})^p (y - \overline{y})^q ds \tag{2}$$

Due to the discretization of CCD equipment, the edge center moment should be considered as written by discrete form. Naturally, the smaller the physical distance along the axis x and the axis y in the imaging plane of the CCD device, the closer the value of the discrete-form edge moment approximates the continuous form. Here we give a set of edge affine [20] invariants as follows:

$$E_0 = \frac{1}{\mu_{00}^2}\left(\mu_{20}\mu_{02} - \mu_{11}^2\right) \tag{3}$$

$$E_1 = \frac{1}{\mu_{00}^7}\left(\mu_{30}^2\mu_{03}^2 - 6\mu_{30}\mu_{12}\mu_{21}\mu_{03} + 4\mu_{30}\mu_{12}^3 + 4\mu_{21}^3\mu_{03} - 3\mu_{21}^2\mu_{12}^2\right) \tag{4}$$

$$E_2 = \frac{1}{\mu_{00}^7}\left[\mu_{20}\left(\mu_{21}\mu_{03} - \mu_{12}^2\right) - \mu_{11}(\mu_{30}\mu_{03} - \mu_{21}\mu_{12}) + \mu_{02}\left(\mu_{30}\mu_{12} - \mu_{21}^2\right)\right] \tag{5}$$

$$\begin{aligned} E_3 = \frac{1}{\mu_{00}^7} (&\mu_{20}^3\mu_{03}^2 - 6\mu_{20}^2\mu_{11}\mu_{12}\mu_{03} - 6\mu_{20}^2\mu_{02}\mu_{21}\mu_{03} \\ &+ 9\mu_{20}^2\mu_{02}\mu_{12}^2 + 12\mu_{20}\mu_{11}^2\mu_{21}\mu_{03} + 6\mu_{20}\mu_{11}\mu_{02}\mu_{03}\mu_{30} \\ &- 18\mu_{20}\mu_{11}\mu_{12}\mu_{21}\mu_{02} - 8\mu_{11}^3\mu_{30}\mu_{03} - 6\mu_{20}\mu_{02}^2\mu_{30}\mu_{12} \\ &+ 9\mu_{20}\mu_{02}^2\mu_{21}^2 + 12\mu_{11}^2\mu_{02}\mu_{12}\mu_{30} - 6\mu_{11}\mu_{02}^2\mu_{30}\mu_{21} + \mu_{02}^3\mu_{30}^2) \end{aligned} \tag{6}$$

$$E_4 = \frac{1}{\mu_{00}^6}\left(\mu_{40}\mu_{04} - 4\mu_{13}\mu_{31} + 3\mu_{22}^2\right) \tag{7}$$

$$E_5 = \left(\mu_{40}\mu_{04}\mu_{22} + 2\mu_{31}\mu_{13}\mu_{22} - 4\mu_{40}\mu_{13}^2 - 4\mu_{04}\mu_{31}^2 - \mu_{22}^3\right) \tag{8}$$

where μ_{pq} is the edge center moment.

3.3 Algorithm Flows

In order to clearly express the texture feature extraction process proposed in this paper, we draw the actual application process shown in Fig. 3.

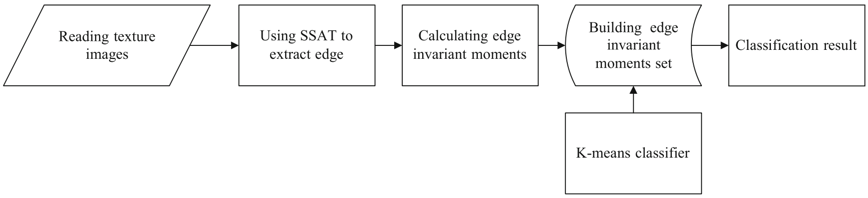

Fig. 3. Flow chart of our proposed scheme

When the texture image is read, our proposed scheme will call SSAT algorithm to extract the corresponding edge image. However, the SSAT itself needs to provide the detection threshold to determine whether it is an edge point. For uniformity, the edge detection threshold is fixed to 0.5. After calculating six EAIM, a set of feature vectors ($E0$, $E1$, $E2$, $E3$, $E4$, $E5$) can be arranged and added to the EAIM sets. And then, the classified recognition results will be obtained by K-means classifier.

4 Simulation and Experiments

In order to test the validity and robustness of the proposed method, we choose Brodatz and KTH-TIPS texture databases. Although the texture images in the above two kinds of texture libraries have changes in rotation, scale, and so on in the acquisition process, they need to be tested for robustness and brightness of the current algorithm. So, a certain degree extension had been added to texture databases. Figure 4 shows a partially expanded texture image.

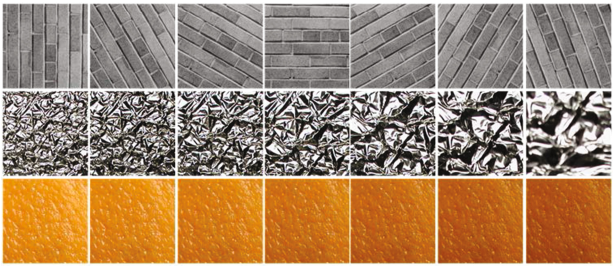

Fig. 4. Some samples in the extended texture database (The first row shows the rotation of the brick. The second row describes the scale change of aluminium foil. The third row is the brightness change of orange peel)

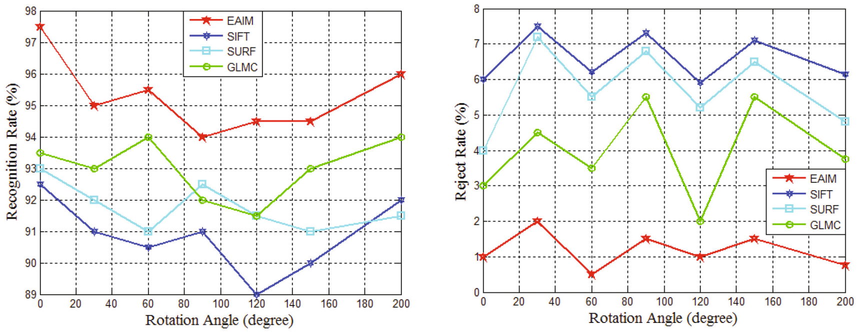

Fig. 5. Comparison of texture feature recognition results during image rotation

Figure 5 shows that the texture recognition rate based on edge affine invariant moment is higher than the other three feature extraction methods while the reject rate is the lowest. The relative error of reject rate of our proposed scheme only reaches 2% and the changing range of recognition rate is from 94% to 97.5%. At the same time, we notice that the recognition and the reject rate are periodic due to the symmetry of rotation.

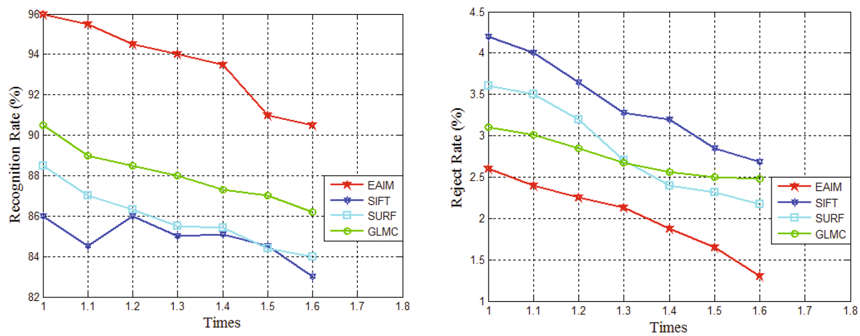

Fig. 6. Comparison of texture feature recognition results during image scale change

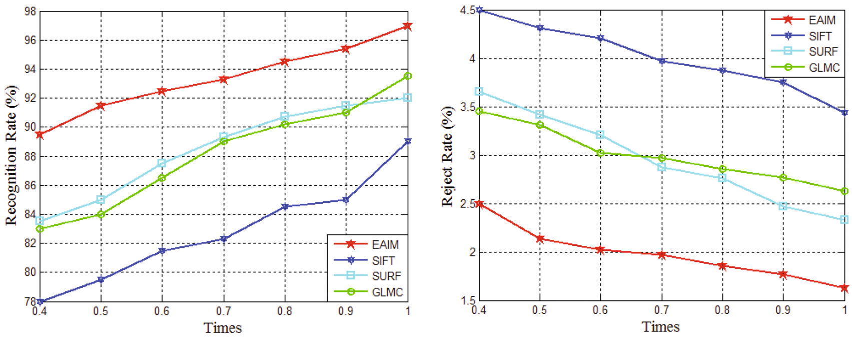

Fig. 7. Comparison of texture feature recognition results during light change

We fix image center and increase the scale of the original image in turn. It can be seen from Fig. 6 that the larger the scale, that is, the more concentrated on local detail, the more similar samples will be obtained. So, it also results in lower reject rate. But the overall loss of information is higher, and thus the recognition rate is lower.

At last, we reduce the brightness of the original image, and use different algorithms to obtain the features of classification and recognition. It can be seen from Fig. 7 that the smaller the brightness, that is, the more difficult to distinguish the local details, the greater the reject rate and because of higher loss of information, the recognition accuracy is low.

It can be seen from the above simulation experiments that the edge affine invariant moment can not only overcome the interference of rotation and scale change, but also is not sensitive to the change of brightness. It is a worthy of generalization of texture feature extraction method.

5 Conclusion and Further Research

In this paper, a new approach is proposed for texture image feature extraction from edge affine invariant moment. The performance of our proposed approach is evaluated by applying EAIM on tow important texture data sets and the results are compared to other well-known descriptors for texture analysis. The algorithm is very simple and possesses less complexity. The proposed approach achieved significant improvements for all tested datasets. To further enhance texture classification performance, some good classifier, such as SVM, will be included in our future research.

Acknowledgments. This work was supported in part by the Major Projects of Nature Science Research in Universities of Anhui (No. KJ2015ZD06), the Key Projects of Nature Science Research in Anhui Universities (No. KJ2015A311, KJ2015A353, KJ2016A802), and Provincial Nature Science Research Project of Anhui Province Higher Education Promotion Plan (No. TSKJ2014B06, TSKJ2015B16).

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