International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.9, No.1 (2016), pp.203-212
http://dx.doi.org/10.14257/ijsip.2016.9.1.19

Content Based Image Retrieval Scheme using Color, Texture and Shape Features

Zhijie Zhao[1], Qin Tian[1], Huadong Sun[1], Xuesong Jin[1] and Junxi Guo[2]

[1]*School of Computer and Information Engineering, Harbin University of commerce*
[2]*School of Software, Harbin Institute of Technology*
Harbin, 150028, China
zhijiezzz@aliyun.com, daisylover.tian@gmail.com

Abstract

A novel approach of Content Based Image Retrieval(CBIR), which combines color, texture and shape descriptors to represent the features of the image, is discussed in this paper. The proposed scheme is based on three noticeable algorithms: color distribution entropy(CDE), color level co-occurrence(CLCM) and invariant moments. CDE takes the correlation of the color spatial distribution in an image into consideration. CLCM matrix is the texture feature of the image, which is a new proposed descriptor that is grounded on co-occurrence matrix to seize the alteration of the texture. Hu invariant moments are frequently used owing to its invariance under translation, changes in scale, and also rotation. The proposed scheme achieves a modest retrieval result by utilizing these diverse and primitive image descriptors, at the same time, the retrieval result is better when use the texture feature alone which we proposed than use gray level co-occurrence. The similarity measure matrix is based upon Euclidean distance.

Keywords: *CBIR; color distribution entropy; color level co-occurrence; invariant moments*

1. Introduction

Interest in the potential of digital images has increased enormously over the last few years, fuelled at least in part by the rapid growth of imaging on the World-Wide Web and sophisticated technology. Users in many professional fields are exploiting the opportunities offered by the ability to access and manipulate remotely-stored images in all kinds of new and exciting ways. However, they are also discovering that the process of locating a desired image in a large and varied collection can be a source of considerable frustration. The problems of image retrieval are becoming widely recognized. Hence, the search for solutions become an active area increasingly.

Content Based Image Retrieval(CBIR)[1,7] means that the search analyzes the content of the image, such as color, texture, rather than the metadata such as keywords, tags. The most directly perceived low-level feature is color. Some approaches have been proposed as an attempt to retrieve similar image among large collection. Swain[2] introduced the method of the color histogram which has proved to be effective and easy to implement. However, it just counts the frequency of the pixels of the image in an intuitive way which does not include any spatial information. Some investigators put forward some propositions to obtain spatial information of color. Fatemeh[3] advanced a scheme using the dynamic distribution entropy of the adjacent pixels to probe into the spatial relationship of color. H.B.kakre[8] tendered a way that reduces the dimension of feature vectors, which obtains the separated images of red, green and blue, and calculates the

ISSN: 2005-4254 IJSIP

quantized histogram, then gets the barycenters to segment each bins to extract color feature.

In order to further improve the retrieval efficacy of the CBIR, more and more investigators attempted to take advantage of various primitive features to fuse for better performance of the retrieval outcome. Cheng[9] chosen Pulse coupled neural network model(PCNN) combined color distribution entropy and texture gradient map to describe the image's features. In [10], color and marginal information are computed by Bi-directional Empirical Mode, but the result, recall ratio indicated unsatisfactory. In [11], successive retrieval steps are adopted, which adapt to all formats of image. The research route is based on the combination of gray-level co-occurrence matrix(GLCM) and entropy, and takes successive map means to achieve the ultimate upshot. The retrieval performance is shown to be better than algorithms in [4] and [5]. In [6], color quantization algorithm with clusters merging are served as capturing color feature, the spatial texture features are extracted using steerable filter decomposition, the pseudo-Zernike moments of an image are used for shape descriptor.

In this paper we suggest a new and effective color image retrieval scheme which adopts the combination of color distribution entropy, color-level co-occurrence matrix and Hu invariant moments to extract features of the image. The rest of this paper is organized as follows. Section 2 describes the color distribution entropy extraction. Section 3 presents the texture representation. In Section 4, the Hu moments based shape descriptor is given. Section 5 provides the similarity measure for image retrieval. The simulation outcome is exhibited in Section 6. Section 7 offers a conclusion.

2. Color Feature Represention

2.1. Annular Color Histogram

Annular color histogram was introduced by Rao[12] to represent color spatial.Suppose A_i is the set of pixels with color bins of an image and $|A_i|$ is the amount of elements in A_i. Let C_i be the centroid and r_i be the radius for each $1 \le j \le N$, we can draw N concentric circles. Let $|A_{ij}|$ be the count of pixels of color bin i inside circle j. Then the annular color histogram can be written as $(|A_{i1}|, |A_{i2}|, \cdots, |A_{iN}|)$.This is illustrated in Figure 1.

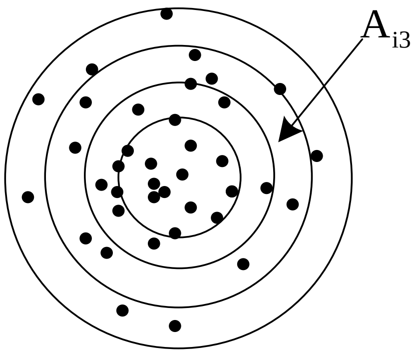


Figure 1. Annular Color Histogram

2.2. Color Distribution Entropy (CDE)

Based on the annular histogram, the normalized histogram can be defined as $\mathbf{P}_i$ where A_{i3} and $P_{ij} = |A_{ij}| / |A_i|$. Then the CDE of the color in i is defined as:

$$H_i(P_i) = -\sum_{j=1}^{N} P_{ij}\, log_2\, P_{ij} \tag{1}$$

Which indicates the disperse degree of the pixel blocks of a color bin in an image. The large value of H_i implies that the distribution of the pixels is dispersed in the image, conversely, the distribution is compacted. We put all the color bins' H_i together to form a feature vector $(H_1, H_2, \ldots, H_n)$, where n is the number of color bins. So we achieve the color feature vector as following:

$$F_c = [H_1, H_2, \cdots, H_n] \tag{2}$$

The extraction of color feature is conducted in HSV color space. The color space is uniformly quantized into nine levels of hue, three levels of saturation and value forming a total 81 bins.

3. Texture Presentation

3.1. Color Level Co-Occurrence Matrix(CLCM)

Gray level co-occurrence matrix(GLCM) is defined by the joint probability density of the pixels' position, which not only reflect the distribution characteristics of luminance, but also mirror the position properties of the pixels that have close or identical brightness. Furthermore, it is about the second-order statistics features of the brightness change.

Although, the computation of texture feature is reduced by one-dimensional GLCM, we used this advantage of computing time for the next steps. Owing to GLCM just considers the gray level of image, it loses other information of the image. Generally, color images are contain more information than gray images. As a matter of course, we reckon that extract the texture feature form color image rather than convert it to gray level. Thus, the color information is taken into account for texture extraction. The feature extraction process of each image is separated into R, G and B planes as shown in Figure 2.

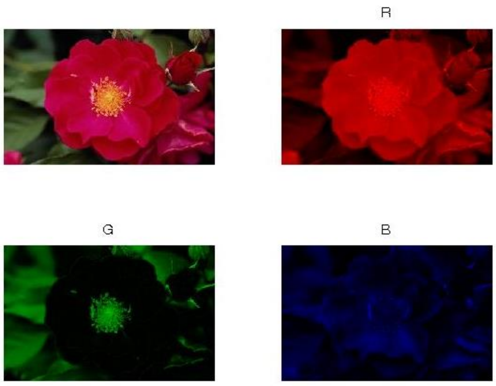


Figure 2. The Retrieval Image with its R, G and B Planes

CLCM is the two dimensional matrix of joint probabilities between two adjacent pixels, separated by a distance d in a given direction θ. Suppose the color scale is L.In order to describe the state of texture in a more intuitive way, we get some matrix parameters derived from co-occurrence matrix, typically are the following:

Energy: $$F_1 = \sum_{i,j} p(i, j, d, \theta)^2 \tag{3}$$

Contrast:
$$F_2 = \sum_{i,j} |i-j|^2 p(i,j,d,\theta) \quad (4)$$

Homogeneity:
$$F_3 = \sum_{i,j} \frac{p(i,j,d,\theta)^2}{1+|i-j|} \quad (5)$$

Entropy:
$$F_4 = -\sum_i \sum_j p(i,j,d,\theta) \log p(i,j,d,\theta) \quad (6)$$

where $p(i,j,d,\theta)$ expresses difference probabilities between pairs in distance d and direction θ, and i,j are the intensities of those pixels of each planes accordingly. The energy denote the degree of uniform distribution of the color image and the texture coarseness. The large value of energy means that the texture changes homogeneous and regular, on the contrary, it has few changes. The contrast signifies the luminance comparison of the certain pixel and its adjacent pixels. Homogeneity measures the alteration of the image's local texture. If different regions' texture lack changes, the value of homogeneity will be large and vice versa. Lastly, the entropy is the measurement of the amount of information possessed by an image. When the majority elements of the co-occurrence matrix have the greatest randomness and dispersed distribution, the entropy is large.

The scheme gets the three channels co-occurrence, then compute the statistics feature which have mentioned in previous section. Subsequently, the feature can be represented as follows:

$$F_t = [F_R, F_G, F_B] \quad (6)$$

Where, F is feature vector and F_R, F_G, R_B are the CLCM matrices of RGB color channels. For the distance $d=1$, $L=16$ and angles $\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$, compute the mean and variance under each angle's statistics feature, which forms the final 1×24 -dimensional feature vector.

4. The Hu Moments based Shape Descriptor

Hu moments which have invariant characters of scale, translation, rotation for region are adopted as shape features. Meanwhile, physically significant of Hu moment is intuitive. The formulations of Hu moments which are used to calculate the feature vector are shown as following:

$$M_1 = \eta_{20} + \eta_{02}$$

$$M_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^{\ 2}$$

$$M_3 = (\eta_{30} - 4\eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2$$

$$M_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{03} + \eta_{21})^2$$

$$M_5 = (\eta_{30} - 3\eta_{12})^2 (\eta_{30} + \eta_{12}) \left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 \right]$$

$$+3(\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03})\left[3(\eta_{30}+\eta_{12})^2-(\eta_{12}+\eta_{30})^2\right] \tag{8}$$

$$M_6=(\eta_{20}-\eta_{02})^2\left[(\eta_{30}+\eta_{12})^2-3(\eta_{21}+\eta_{03})^2\right]$$

$$+4\eta_{11}(\eta_{30}+\eta_{12})(\eta_{21}+\eta_{03})$$

$$M_7=(3\eta_{21}-\eta_{03})(\eta_{30}+\eta_{12})\left[(\eta_{30}+\eta_{12})^2-3(\eta_{21}+\eta_{03})^2\right]$$

$$-(\eta_{30}-3\eta_{12})(\eta_{21}+\eta_{03})\left[3(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2\right]$$

From the above equation (8), the Hu moments are made up of second-order and third-order of the central moment. In the equation (8), η_{pq} stands for the normal central moment.

$$\eta_{pq}=\frac{\mu_{pq}}{\mu_{00}^{(p+q)/2+1}} \tag{9}$$

Effectively, μ_{pq} represents the $(p+q)$ order centre moment.

$$\mu_{pq}=\sum_x\sum_y(x-x_c)^p(y-y_c)^q f(x,y) \tag{10}$$

(x,y) is the coordination of the pixels in the image region, and $f(x,y)$ denotes the corresponding gray value. (x_c,y_c) signifies the barycentric coordinate of the image.

5. Similarity Measure

After the extraction of color, texture and shape feature vectors, the retrieval processes should combine these three feature vectors to calculate the similarity between the query image and image database to find the targets. Accordingly, the retrieval result is a list of images ranked by their similarities with query image.

5.1. Color Feature Similarity Measure

With the reference to definition of similarity matrix in [12], the distance of images Q and I can be written as

$$S_{color}(Q,I)=\sum_{i=1}^{N}min\left(h_i^Q,h_i^I\right)\times\frac{min\left(E_i^Q,E_i^I\right)}{max\left(E_i^Q,E_i^I\right)} \tag{11}$$

The similarity metric comprises two parts; the former part, $min\left(h_i^Q,h_i^I\right)$, which is histogram intersection which measures the similarity between h_i^Q and h_i^I, while the later $min\left(E_i^Q,E_i^I\right)/max\left(E_i^Q,E_i^I\right)$ measures the similarity of spatial distribution of bins.

5.2. Texture Feature Similarity Measure

The texture feature similarity is given by

$$S_{texture}(Q,I)=\sqrt{\sum_{i=1}^{24}\left(F_i^Q-F_i^I\right)^2} \tag{11}$$

where F_i^Q denotes the texture feature of query image and F_i^I denotes those of the image database.

5.3. Shape Feature Similarity Measure

The measurement of shape feature similarity is shown as follows

$$S_{shape}(Q,I)=\left(\sum_{i=1}^{7}\left(M_i^Q-M_i^I\right)^2\right)^{\frac{1}{2}} \tag{12}$$

where M_i^Q and M_i^I denote the shape features of the query image Q and the image I of the image database respectively .

In order to compare different subfeatures, it is essential to normalize the similarity distance. The overall similarity is the sum of weighted similarities for normalized distance. The overall similarity is calculated by

$$S = w_c S_c + w_t S_t + w_s S_s \tag{13}$$

where w_c, w_t and w_s determine the contribution of these three features respectively in calculating the similarity. For the selection of these three weights, there's no concrete specification, which is decided by the experience of the users.

6. Experiment Results

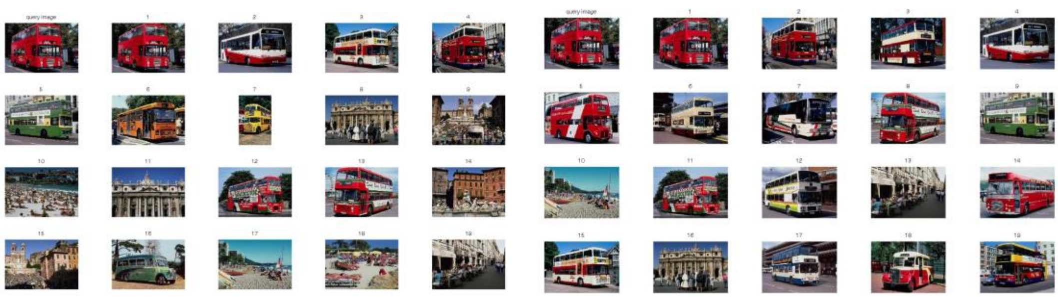
In this section, we present the experimental result of our work. The image database we choose the same as used by the previous researches, and it contains 1000 images, which include 10 different sets of images that made up of people, natural scenes, architecture, vehicles, animals, plant, *etc*.

The experiments were carried out on a Pentium VI, 3.2GHz processor with 4 GB RAM on the platform of MATLAB. The retrieval accuracy was assessed in terms of precision and recall ratio which are difined as follows:

$$precision = \frac{n}{K} \tag{14}$$

where n is the number of relevant images in retrieved images, K is the amount of retrieved images.

The image in the top left hand corner of each retrieval result is the query images, and rest of the amount images are the mapping images according to the distances ranking which measure the similarity between queries and image set.



(a) (b)

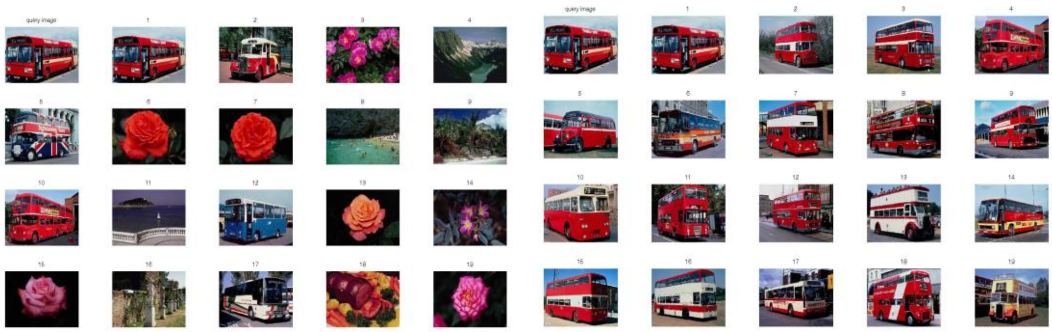
(c) (d)

Figure 3. (a) & (C) GLCM, (c) & (d) the Proposed CLCM

Table 1. The Retrieval Precision[%] of GLCM & CLCM

P L	20	30	40	50	60	70	80
GLCM	75. 0	60. 0	55. 0	52. 0	50. 0	42. 9	42. 5
CLCM	100. 0	96. 7	92. 5	92. 0	85. 0	82. 9	81. 2

(a) (b)



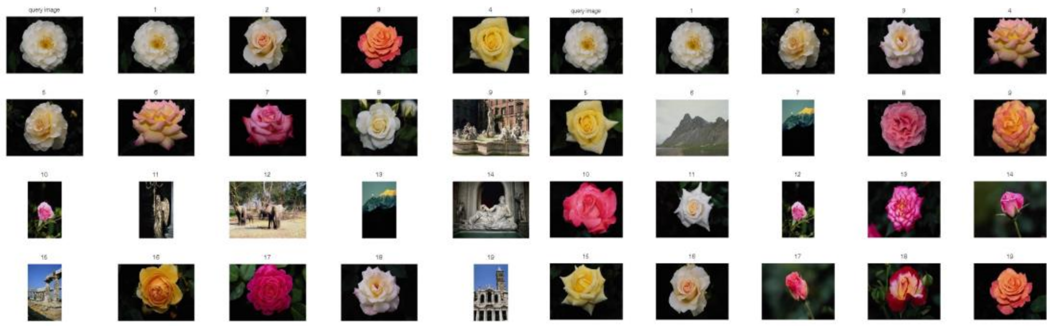
(c) (d)

Figure 4. (a) CDE, (b) CLCM, (c) Hu moments, (d) the Proposed Method

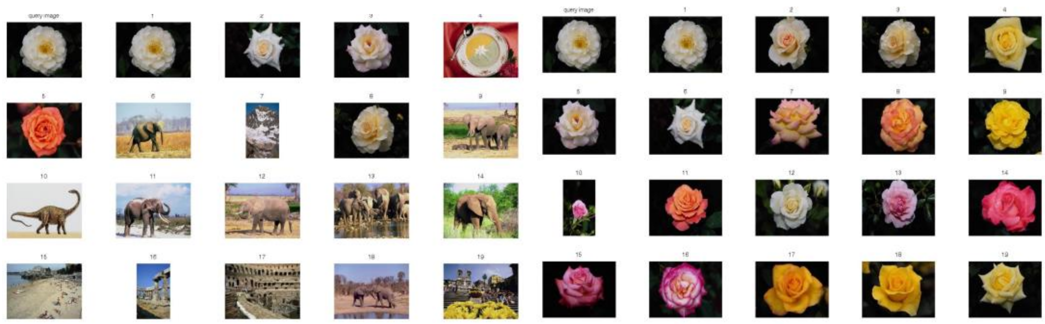
(a) (b)

(c) (d)

Figure 5. (a) CDE, (b) CLCM, (c) Hu Moments, (d) the Proposed Method



(a) (b)



(c) (d)

Figure 6. (a) CDE, (b) CLCM, (c) Hu Moments, (d) the Proposed Method

P \ L	20	30	40	50	60	70	80
black man	80.0	73.3	77.5	70.0	63.6	54.4	53.7
beach	85.0	76.6	70.0	66.0	61.4	57.1	55.0
architecture	85.0	76.6	67.5	62.0	61.3	57.1	57.5
bus	100.0	100.0	92.5	88.0	81.6	80.0	75.0
dinosaur	95.0	90.0	85.0	84.0	86.0	87.0	86.2
elephant	95.0	76.6	70.0	82.0	68.3	65.7	63.7
flower	90.0	93.3	93.3	90.0	85.0	81.4	77.5
horse	100.0	86.6	85.0	78.0	73.3	70.0	62.5
mountain	85.0	90.0	65.0	64.0	60.0	54.2	53.7
food	90.0	76.6	90.0	85.0	78.3	72.8	67.5
average	90.5	84.0	79.8	76.9	71.9	68.0	65.2

Table 2. Retrieval Performance based on Precision[%]

7. Conclusion

A novel approach for image retrieval by combining color, texture and shape features has been presented. The simulation results showed that our method did good on precision ratio. Especially when the targets in queries are clear and distinct, the retrieval results manifest the scheme's efficiency. At the same time, the texture feature that is mended as CLCM which is did better than GLCM from the retrieval results. However, it also shows that there is a substantial improvement in the performance of image retrieval. When the scene of query images are complex, the low visual features are insufficient to represent them. So, further enhancement can be obtained by utilizing high-level visual features such as semantic feature.

Acknowledgements

This research was supported by the free fund project for returned oversea of Human resources and social security ministry, and Nature Science Foundation of Heilongjiang Province (F201245). Graduate innovation project (YJSCX2014-315HSI)

References

[1] R. Datta, J. Li and J. Z. Wang, "Image Retrieval: Ideas, Influences, and Trends of the New Age [J]", ACM Computing Surveys **(2008)**, vol. 40, no. 2, pp. 1-60.

[2] M. J. Swain and D. H. Ballard, "Color indexing", International Journal on Computer Vision, vol. 7, no. 1, **(1991)** pp. 11-32.

[3] F. Alamdar and M. R. Keyvanpour, "A New Color Feature Extraction Methods Based on Dynamic Color Distribution of Neighborhoods", IJCSI International Journal of Computer Science Issues, vol. 8, Iss. 5, no.1, **(2013)**, pp. 42-48.

[4] W-J. Huang, P. S. Yu and V. S. Tseng, "Efficient Relevance Feedback for Content Based Image Retrieval by Mining User Navigation Patterns", vol. 23, Iss. 3, **(2011)**, pp. 360-372.

[5] W. Khan, S. Kumar, N. Gupta and N. Khan, "A proposed Method for Image Retrieval using Histogram values and Texture Descriptor Analysis", International Journal of Soft Computing and Engineering (IJSCE) ISSN:2231-2307, vol.1, Iss. 2, **(2011)**.

[6] X. Wang, Y. Yu and H. Yang, “An effective image retrieval scheme using color, texture and shape feature”, Computer Standards & Interfaces, **(2011)**, pp. 59-68.
[7] M. Madugunki, D. S. Bormane, S. Bhadoria and C. G. Dethe, “Comparison of different CBIR techniques”, the 3rd International Conference on Electronics Computer Technology (ICECT), **(2011)**, pp. 372-375.
[8] H. B. Kekre and K. Sonawane, “Use of Equalized Histogram CG on Statistical Parameters in Bins Approach for CBIR”, IEEE International Conference on Advances in Technology and Engineering (ICATE), **(2013)** pp. 1-6.
[9] C. Yang and X. Gu, “Combining PCNN with color distribution entropy and vector gradient in feature extraction”, The 8th IEEE International Conference on Natural Computation (ICNC), **(2012)**, pp. 207-211.
[10] P. Shrinivasacharya and M. V. Sudhamani, “Content Based Image Retrieval by Combining Median Filtering”, BEMD and Color Technique, Proceedings of International Conference on Advances in Computing Advances in Intelligent Systems and Computing, vol. 174, **(2012)**, pp. 969-975.
[11] K. V. Shriram, Dr. P. L. K Priadarsini, M. Gokul, V. Subashri and R. A. Sivaraman, “Nnovel Approach Using T.H.E.S Methodology for CBIR, IEEE International Conference on Signal Processing and Pattern Recognition (ICSIPR), **(2013)** pp. 10-13.
[12] S. Lim and G. J. Lu, “Spatial statistics for content based image retrieval”, In: Proceedings of the International Conference on Information Technology: Computers and Communications, Las Vegas, Nevada, **(2003)**, pp. 28–30.

Authors

Zhijie Zhao, He was born in Harbin, China, in 1963. He is currently a professor with the School of Computer and Information Engineering at the Harbin University of Commerce, China. He achieved his B.S. and M.S.Degree from Harbin University of Science and Technology, China, in 1985 and 1988, and obtained his phD from HIT in 2008, respectively. His research interests include image processing and intelligence information processing.

Qin Tian, She received her B.S. degree from the School of Engineering and Technology at the Hubei University of Technology, China, in 2012. Currently, she is proceeding the M.S. degree. Her research interests include image retrieval and signal processing.

Huadong Sun, He is currently an assistant professor in the the School of Computer and Information Engineering at the Harbin University of Commerce, China. He achieved his B.S., M.S. and phD from Harbin Institute of Technology, China in 2002, 2004 and 2009, respectively. His research interests include image processing and intelligence information processing.

