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Fast Feature Extraction Based on Multi-feature Classification for Color Image

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Abstract. *Feature extraction and representation is one of the most important issues in Content based image retrieval. There exist many mature algorithms using several features like shape,texture,color and text complete image retrieval. While the retrieval accuracy and speed are gaining importance as image databases continue to grow in size. This paper proposes a fast feature extraction algorithm which improve the retrieval speed greatly. The proposed feature is based on multi-feature classification, where we classify image blocks into different categories according to the brightness, contrast and edge orientation information of each blocks. Firstly, all training vectors are classified into 64 categories based on a three-level classifier including a brightness classifier ,a contrast classifier and an edge classifier. Then, the training vectors in each category are sorted based on their norm values and divided into groups. Finally, we obtain the classification indices as the final feature. In our simulation experiments, we compare not only the retrieval accuracy but also retrieval speed, and the comparison results show that our method can retrieve relevant images more effectively and efficiently.*
Keywords: Content-based image retrieval, Multi-feature classification, brightness, contrast,edge orientation

1. **Introduction.** Nowadays, it is a challenging task to effectively and efficiently retrieve relevant images from large-scale databases or over the Internet. In general, image retrieval can be classified into two categories, i.e., Text-based Image Retrieval (TBIR) and Content-based Image Retrieval (CBIR). Traditional TBIR retrieves relevant images based on keywords, and thus annotation is an essential step before retrieval. CBIR overcomes the disadvantage of TBIR by extracting visual contents such as colour [1], texture [2] and shape [3] and spatial relationship from images, which are more intuitive and more fundamental than keywords. In the past fifteen years, many studies have been devoted to image retrieval techniques on compressed-domains such as DCT [4], DWT [5], fractal coding, block truncation coding (BTC) [6] and Vector Quantization (VQ) [7]. In [4], Lu and Burkhardt obtained VQ index histogram features after segmenting each 8×8 DCT block into four vectors and quantizing them using four corresponding codebooks. In [5], Wang et al. progressively retrieved image with three steps based on four DWT lowest

resolution subbands. In [6], Yu et al. retrieved colour images according to an effective feature obtained from the BTC and VQ compressed data. VQ has received great attention in the last several decades due to its relatively simple compression structure and low decoding computation, and thus in [7], Uchiyama et al. extracted features from VQ index tables. In [8], Chen et al. classified image blocks into different classes and each block is then encoded with the VQ codebook that is designed in advance specifically for the class that the block belongs to. Experiments have shown that classified VQ (CVQ) outperforms VQ in terms of perceptual quality and complexity.

Currently, rapid and effective searching for desired images from large-scale image database becomes an important and challenging research topic. Many signal feature extraction methods cannot describe an image comprehensively. Therefore, it is suggested to use the fusion of visual features to realized it effectively. However, many existing image retrieval approaches are of high computational complexity and cost. In order to reduce the complexity and cost, our former paper [9] classified image blocks into nine categories according to their edge orientation patterns (EOPs), and we combined our EOP-histogram (EOPH)-based features with the traditional VQIHs based features to improve the recall and precision performance. This scheme reminds us that we can extract features from images simply based on classification. Inspired by the methods which classify the image blocks into different categories, this paper proposes a simple feature which integrates with the brightness, contrast and edge information to retrieve relevant images more effectively and efficiently.

2. **Proposed Image Retrieval Scheme Based on Multi-feature Classification Histogram.** The multi-feature based CBIR system extracts color, shape and texture features of the image. The color is the most widely used visual property of the image. It is a robust descriptor as it is uniform with respect to scaling, translation, and rotation of an image. And the color feature can be extracted from Color histogram, color moment and color set and so on. Texture or gray-level features depicts visual patterns in an image and describes how they are spatially located. Different from the gray and color image characteristics, texture reflects the relationship between adjacent pixels and its surrounding space. The shape of an object or region in an image is represented by shape features. These features are commonly extracted and obtained after image segmentation. Shape features are extracted from two kinds of methods, one kind is contour features, another kind is regional characteristics. Contour features is mainly aimed at the outer boundary of the object in an image, while the regional feature is mainly related to the whole shape area.

The fundamental idea of our scheme is to divide an input image into blocks and classify image blocks into categories based on multiple features and then obtain a histogram for each image. In this paper, for each colour component (such as Y,Cb,Cr) of an input colour image, we segment it into non-overlapping 4×4-sized blocks. Then, we carry out the brightness classification (4 classes), contrast classification (2 classes) and edge orientation pattern (EOP) classification (8 classes) respectively on each image block. After classifications, all the image blocks can be classified into 64 ($4 \times 2 \times 8$) classes. And thus we can obtain a multi-feature classification histogram (MFCH) based on the number of blocks belonging to each class. As a result, we can extract three 64-bin MFCHs for each input image described in the YCbCr colour space, and in total, our MFCH based feature has a dimension of 192. The overall feature extraction diagram is shown in Fig. 1.

2.1. **Brightness Feature.** Now we turn to describing the detailed classification process. As we know, colour can describe the image more dominantly and distinguishably among

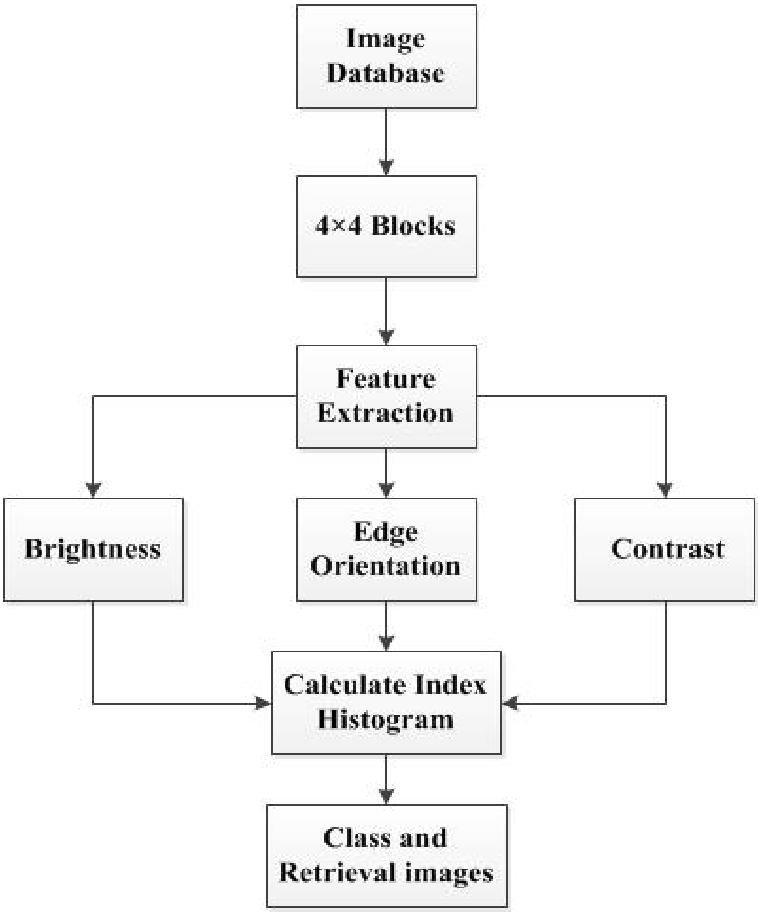

FIGURE 1. The feature extraction diagram of proposed algorithm

different visual features, so it is widely employed to retrieve images. Colour histogram [10] is a representation of the distribution of colours in an image. Here, we apply the brightness of the non-overlapping 4×4 blocks to represent the colour feature of the sub-blocks. We compute the average pixel value for the k-th 4×4 block $x(m, n)$ denoted as b_k.

$$b_k = \frac{1}{16} \sum_{m=0}^{3} \sum_{n=0}^{3} x(m, n) \tag{1}$$

Here $x(m, n)$ denotes the pixel value at the coordinate (m, n), and b_k is the average pixel value of the k-th 4×4 block.

For all non-overlapping 4×4 blocks, the brightness classification process can be described as follows: Firstly, the brightness of each image block is calculated according to Eq.(1), and then all the image blocks are classified into four categories according to the brightness distribution: (1) $0 \le b_k < 64$, (2) $64 \le b_k < 128$, (3) $128 \le b_k < 192$, (4) $192 \le b_k < 256$.

2.2. **Contrast Feature.** Contrast is the difference in colour and light between parts of an image and the contrast of an image block measures how the pixel value in the block is distributed, which can reflect the texture of shadow depth as well as image clarity. The larger the contrast is, the deeper the texture is. We define the contrast of each block as c_k:

$$c_k = \frac{1}{16}\sum_{m=0}^{3}\sum_{n=0}^{3}|[x(m,n) - b_k]| \tag{2}$$

Thus we classify the input vector into two categories: the high-contrast or smooth class based on the threshold 3.0 (which is selected based on a number of experiments based on many images) as follows:

$$\begin{cases} x(m,n) \in High\ contrast\ category & c_k \geq 3 \\ x(m,n) \in Smooth\ category & c_k < 3.0 \end{cases} \tag{3}$$

2.3. **Edge Orientation Feature.** As the edge orientation information is vital for an image. Inspired by the Structured Local Binary Kirsch Pattern (SLBKP) proposed in [12] that adopts eight 3×3 Kirsch templates to discriminate eight edge orientations, we propose the Edge Orientation Patterns (EOPs) based histogram is a kind of simple edge feature in our previous Letter [9]. Here we still take them as one of our classification indicators, which can reflect the edge orientation distribution of an image. Following are the eight 4×4 templates for EOP classification.

$$\begin{gathered}
\mathbf{E}_1 = \begin{bmatrix} -4 & 2 & 2 & 2 \\ -4 & 0 & 0 & 2 \\ -4 & 0 & 0 & 2 \\ -4 & 2 & 2 & 2 \end{bmatrix}, \mathbf{E}_2 = \begin{bmatrix} 2 & 2 & 2 & 2 \\ 0 & 0 & 2 & 2 \\ -4 & -4 & 0 & 2 \\ -4 & -4 & 0 & 2 \end{bmatrix}, \mathbf{E}_3 = \begin{bmatrix} 2 & 2 & 2 & 2 \\ 2 & 0 & 0 & 2 \\ 2 & 0 & 0 & 2 \\ -4 & -4 & -4 & -4 \end{bmatrix}, \\
\mathbf{E}_4 = \begin{bmatrix} 2 & 2 & 2 & 2 \\ 2 & 2 & 0 & 0 \\ 2 & 0 & -4 & -4 \\ 2 & 0 & -4 & -4 \end{bmatrix}, \mathbf{E}_5 = \begin{bmatrix} 2 & 2 & 2 & -4 \\ 2 & 0 & 0 & -4 \\ 2 & 0 & 0 & -4 \\ 2 & 2 & 2 & -4 \end{bmatrix}, \mathbf{E}_6 = \begin{bmatrix} 2 & 0 & -4 & -4 \\ 2 & 0 & -4 & -4 \\ 2 & 2 & 0 & 0 \\ 2 & 2 & 2 & 2 \end{bmatrix}, \\
\mathbf{E}_7 = \begin{bmatrix} -4 & -4 & -4 & -4 \\ 2 & 0 & 0 & 2 \\ 2 & 0 & 0 & 2 \\ 2 & 2 & 2 & 2 \end{bmatrix}, \mathbf{E}_8 = \begin{bmatrix} -4 & -4 & 0 & 2 \\ -4 & -4 & 0 & 2 \\ 0 & 0 & 2 & 2 \\ 2 & 2 & 2 & 2 \end{bmatrix}
\end{gathered} \tag{4}$$

Above eight templates are used to represent eight edge orientations, i.e., $E_1 \sim E_8$ denote the edge orientations of 0^o, 45^o, 90^o, ..., 315^o respectively. Assume the input image $\boldsymbol{X}$ is divided into non-overlapping 4×4 blocks, the EOP classification process can be stated as follows: Firstly, we perform eight 4×4 edge orientation templates on each 4×4 block $x(m,n)$, $0 \leq m < 4$, $0 \leq n < 4$, obtaining an edge orientation vector $v = (v_1, v_2, ..., v_8)$ with its components $v_i (1 \leq i \leq 8)$ being computed as follows:

$$v_i = |\sum_{m=0}^{3}\sum_{n=0}^{3} x(m,n) * e_i(m,n)| \qquad 1 \leq i \leq 8 \tag{5}$$

where $e_i(m,n)$ stands for the element at the position (m,n) of the template $\mathbf{E}_i$. And then we get the maximum component of its edge orientation vector $\boldsymbol{v}$, and the block $x(m,n)$ belongs to one of eight edge orientations according to Eq (6).

$$x(m,n) \in The\ i-th\ category \qquad if \quad i = \arg\max_{1\leq i\leq 8}(v_i). \tag{6}$$

That is to say, we can classify each block into one of the eight categories according to its edge orientation.

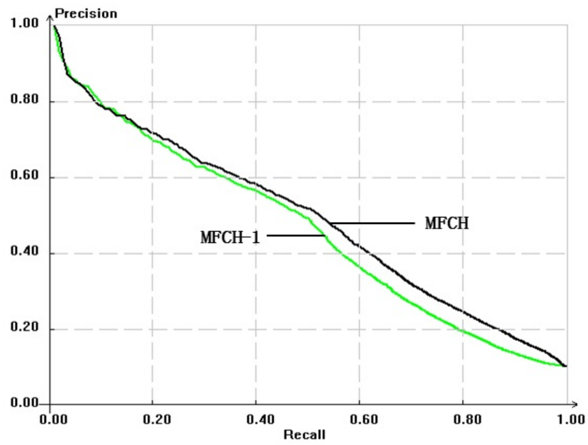

Figure 2. Comparisons of the average P-R curves for MFCH and MFCH-1 with the same dimension of 192

3. **Experiment Results.** To show that the proposed features can retrieve images more effectively, we compared our features with two kinds of traditional features, i.e., spatial-domain colour histogram (SCH)[13] and VQ index histogram (VQIH)[14] and two other features, i.e., SLBKP [12] and SLBHP [15]. In all schemes, the YCbCr colour space is adopted and the feature dimension is 192. Here, we do experiments on two standard databases [11]. One consists of 1000 images with the size of 384×256 or 256×384, which are classified into 10 categories, each containing 100 images. The other one consists of 10000 image with the size of 256×256, which are classified into 25 categories, each containing 400 images.

We choose the precision-recall (P-R) curves to evaluate the retrieval effectiveness. In general, precision and recall are computed as below in eq(7):

$$\begin{aligned} prcision &= \frac{No.relevant\ images}{No.images\ returned} \\ recall &= \frac{No.relevant\ iamges}{No.sum\ of\ each\ image\ category} \end{aligned} \tag{7}$$

In our experiments, we firstly choose the standard database with 1000 images. Combined with the probability distribution of brightness and contrast of image blocks, we test the image retrieval efficiency based on two different block classification schemes.

Classification scheme 1: Classify the images blocks into four categories according to brightness (1) $0 \le b_k < 64$, (2) $64 \le b_k < 128$, (3) $128 \le b_k < 192$, (4) $192 \le b_k < 256$; Classify the image blocks into two categories according to contrast (1) $0 \le c_k < 10.0$, (2) $c_k \ge 10.0$; and classify the image blocks into eight categories according to the EOP. The feature based on this classification scheme is defined as MFCH.

Classification scheme 2: Classify the images blocks into two categories according to brightness (1) $0 \le b_k < 128$, (2) $128 \le b_k < 256$; Classify the image blocks into four categories according to contrast (1) $0 \le c_k < 5.0$, (2) $5.0 \le c_k < 10.0$, (3)$10.0 \le c_k < 15.0$, (2) $c_k \ge 15.0$; And classify the image blocks into eight categories according to the EOP. And we define the feature based on the classification scheme as MFCH-1 based image retrieval.

That is to say, we classify the image blocks into 64 categories according to the two classification schemes, and the comparison of the average $P-R$ curves among the MFCH and the MFCH-1 based features are shown in Fig. 2. Seen from Fig. 2, we can say that

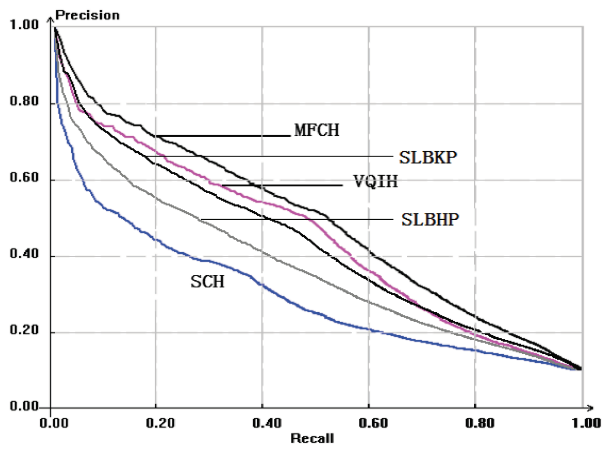

FIGURE 3. Comparisons of the average P-R curves among SCH, VQIH, SLBHP, SLBKP and MFCH with the same dimension of 192

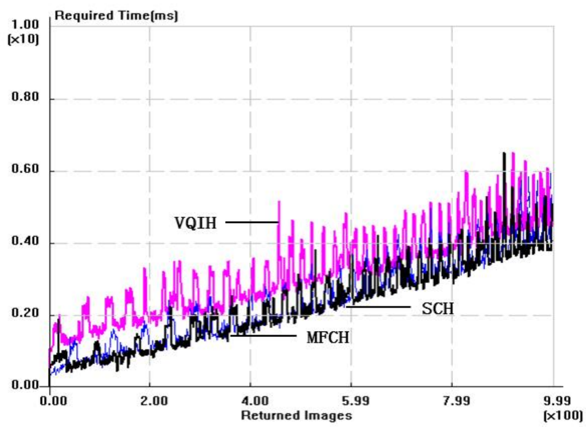

FIGURE 4. Comparisons of the feature extraction time needed for SCH, VQIH and MFCH for the database with 1000 images

the feature based on classification scheme 1 performs better than classification scheme 2. So, we will choose the MFCH based classification scheme as our experimental scheme to compare with the other existing image retrieval methods.

Fig. 3 shows the comparison of the average P-R curves among the SCH, VQIH, SLBKP, SLBHP and our MFCH based features. Combined with the above experimental results, we can easily find that our feature can get a much better performance in precision and recall. As a single feature is insufficient to fully represent the content of an image, while in our method, the colour, texture and edge orientation features are integrated. Thus, the MFCH based feature can perform better than the SCH, VQIH, SLBHP and SLBKP based schemes. That is to say, our feature can retrieve relevant images more effectively.

In addition, fast retrieval is becoming more and more important with the increase of image database sizes, so the efficiency of image retrieval is of vital importance. For the image database consisting of 1000 images, we test the time needed for SCH, VQIH and MFCH based schemes and the comparison results are shown in Fig. 4. Seen from the results in Fig. 4, we can find that, compared to the VQIH based scheme, our scheme can save much more feature extraction time. And our scheme is as fast as the SCH scheme owing to simple classification. In order to compare the retrieval efficiency of these two

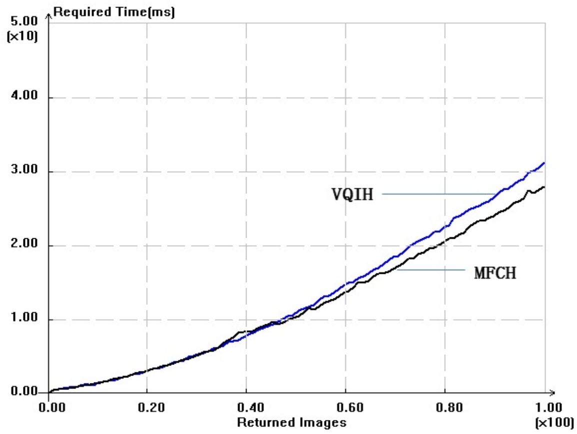

FIGURE 5. Comparisons of the feature extraction time needed for SCH, VQIH and MFCH for the database with 10000 images

algorithms more clearly, we also do experiments on the larger image database consisting of 10000 images. Fig. 5 shows the experimental comparison results in terms of feature extraction time for the database consisting of 10000 images.

Seen from the trend of the two curves, as the image database increasing, our proposed method performs better than the SCH based method. The complexity of different algorithms are different, however seen from the practical retrieval results, our proposed method can largely improve the efficiency of image retrieval. In summary, we can say that our retrieval scheme can retrieve relevant images more efficiently.

4. **Conclusion.** This paper presents a fast feature extraction scheme for image retrieval based on simple feature classification. The experimental results based on two standard image databases show that our feature outperforms traditional SCH, VQIH, SLBHP and SLBKP features in colour image retrieval in precision-recall and our feature can also retrieve images faster. Future work will pay attention to how to select various kinds of simple features [16-18] to form a feature grid as a more discriminative and powerful feature descriptor.

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REFERENCES

[1] A. R. Kumar, D. Saravanan. Content based image retrieval using color histogram, *International Journal of Computer Science and Information Technologies*, vol.4, no.2, pp. 242-245, 2013.
[2] M. R. Hejazi, Y. S. Ho. An efficient approach to texture based image retrieval, *International Journal of Imaging Systems and Technology*, vol. 17, no.5, pp. 295-302, 2007.
[3] D. S. Zhang, and G. Lu, Shape-based image retrieval using generic Fourier descriptor, *Signal Processing: Image Communication*, vol. 17, no.10, pp. 825-848, 2002.
[4] Z. M. Lu, H. Burkhardt. Colour image retrieval based on DCT-domain vector quantisation index histograms, *Electronics Letters*, vol. 41, no. 17, pp. 956-957, 2005.
[5] J. Z. Wang, G. Wiederhold, O. Firschein, S. X. Wei. Wavelet-based image indexing techniques with partial sketch retrieval capability, *IEEE International Forum on Research and Technology Advances in IEEE*, pp. 13-24, 1997.
[6] F. X. Yu, H. Luo, Z. M. Lu. Colour image retrieval using pattern co-occurrence matrices based on BTC and VQ, *Electronics Letters*, vol. 47, no. 2, pp. 100-101, 2011.

[7] T. Uchiyama, M. Yamaguchi, N. Ohyama. Multispectral image retrieval using vector quantization, *Proceedings of IEEE International Conference on Image Processing*, Thessaloniki, Greece, vol. 1, pp. 30-33, 2001.
[8] H. H. Chen, J. J. Ding, H. T. Sheu. Image retrieval based on quadtree classified vector quantization, *Multimedia Tools and Applications*, vol. 72, no. 2, pp. 1961-1984, 2014.
[9] Z. M. Lu, Y. P. Feng. Image retrieval based on histograms of EOPs and VQ indices, *Electronics Letters*, vol. 52, no.20, pp. 1683-1684, 2016.
[10] M. Singha, K. Hemachandran, A. Paul. Content-based image retrieval using the combination of the fast wavelet transformation and the colour histogram, *IET Image Processing*, vol. 6, no.9, pp. 1221-1226, 2012.
[11] Li, J.: Photography image database. http://www.stat.psu.edu/ jiali/index.download.html
[12] G.Y. Kang, S.Z. Guo , D.C. Wang , L.H. Ma , Z.M.Lu, Image retrieval based on structured local binary kirsch pattern,*IEICE Trans Inf Syst*,vol.96, no.5, pp.1230-1232,2013.
[13] P.S. Suhasini, Krishna. K, and I.M.Krishna,CBIR using colour histogram processing, J. Theor. Appl. Inf. Technol, vol. 6, no.1, pp. 116-122, 2009.
[14] A. Gersho, and R.M. Gray, Vector quantization and signal compression, *Springer Science and Business Media*, New York, 2012.
[15] S. Z. Su, S. Y. Chen, S. Z. Li, S. A. Li, D. J. Duh, Structured local binary Haar pattern for pixel-based graphics retrieval, *Electronics Letters*, vol. 46, no.14, pp. 996-998, 2010.
[16] Y. L. Qiao, Z. M. Lu, J. S. Pan, and S. H. Sun, Spline wavelets based texture features for image retrieval, *International Journal of Innovative Computing, Information and Control*, vol. 2, no. 3, pp. 653-658, 2006.
[17] J. S. Pan, Q. Feng, L. Yan, and J. F. Yang, Neighborhood feature line segment for image classification, *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 25, no. 3, pp. 387-398, 2015.
[18] Q. Feng, X. Zhu, and J. S. Pan, Novel classification rule of two-phase test sample sparse representation, *OPTIK-International Journal for Light and Electron Optics*, vol. 125, no. 19, pp. 5825-5832, 2014.