Image Retrieval Based on Texture Direction Feature and Online Feature Selection

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Abstract. In this paper, a new method for image texture representation is proposed, which represents image content using a 49 dimensional feature vector through calculating the variation of texture direction and the intensity of texture. In addition, the texture feature is grouped into a feature set with some other image texture representation methods, and then a new online feature selection method with a novel discrimination criterion is presented. We test the discriminating ability of every feature in the feature set utilizing the discrimination criterion, and select the optimal feature subset, which expresses image content in an even better fashion. The results of the computer simulation experiments show that the proposed feature extraction and feature selection method can represent image content effectively, and improve the retrieval precision visibly.

Keywords: Image retrieval, texture direction feature, online feature selection, discrimination criterion.

1 Introduction

With the development of computer technology, a mass of multimedia information grows out of Internet. We can get these datum on the Internet, but at the meanwhile, it becomes harder and harder for us to find useful information. In order to obtain datum that users are concerned about, content based image retrieval (CBIR) becomes a research focus in the field of computer vision. In tradition, image retrieval systems fulfill image indexing via keywords annotation, but it needs a good deal of manual operation, and keywords annotation depends much on people who label the images, there may be different understanding of the same image among different people. Compared with text-based image retrieval (TBIR), CBIR system extracts image visual features automatically.

For the past few years, researchers present many feature extraction methods. Liu *et al.* build micro-structure descriptor (MSD) [1] according the similarity of edge direction and statistic characteristic of color feature, so it blends color, texture, shape and spatial information together. Yang *et al.* describe image content with 4-5 kinds of prominent colors, and extracts dominant color descriptor (DCD) [2]. Balasubramani *et al.* extract edge histogram descriptor (EHD) [3]

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via calculating edge distribution of an image block with different edge operators. Young *et al*. calculate block difference of inverse probabilities (BDIP) and block variation of local correlation coefficients (BVLC) [4] on an image block, and then get the corresponding texture feature.

The feature selection technology basically narrows the semantic gap by selecting a feature subset. Feature selection methods are classified into Filter-based feature selection [5] and Wrapper-based feature selection [6]. The evaluation criterion of Filter-based feature selection is determined by properties of the data itself, so it is independent of learning algorithm. The frequently-used Filter-based feature selection algorithms are Relief algorithm [7] and Mitra algorithm [8]. Wrapper-based feature selection evaluates the performance of feature subset using learning algorithms, and then chooses the feature subset with higher precision rate.

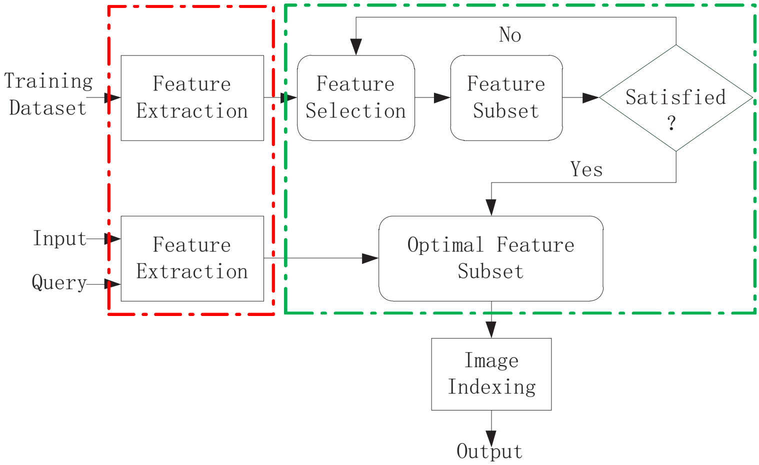


Fig. 1. Image Retrieval System Based on Feature Extraction and Selection.

In this paper, a new image retrieval method is proposed by means of combining feature extraction and selection. First, we compute the direction variation and intensity of pixel values in an image block, which is divided into different texture patterns. Two image blocks in neighborhood make up a pattern pair, we obtain the Texture Direction Descriptor by counting the number of the pattern pairs. Then, Texture Direction Descriptor constitutes an image feature set with other image features. Test the discriminating ability of every feature utilizing a discrimination criterion [8][9], and select the optimal feature subset with the best discriminating ability. The system chart of the proposed image retrieval system is shown in Fig. 1.

The outline of the paper is as follows. Section 2 presents the feature extraction approach in detail. Section 3 proposes the online feature selection method. Section 4 provides the results of experiments. Conclusions are given in Section 5 at the end of the paper.

2 Texture Direction Feature

In this paper, we propose a new texture feature extraction method. Methods for texture feature extraction generally obtain the texture image first, and then make a statistical analysis of the texture image. Different from previous methods, the proposed method calculates the variation of texture direction and intensity on original image directly.

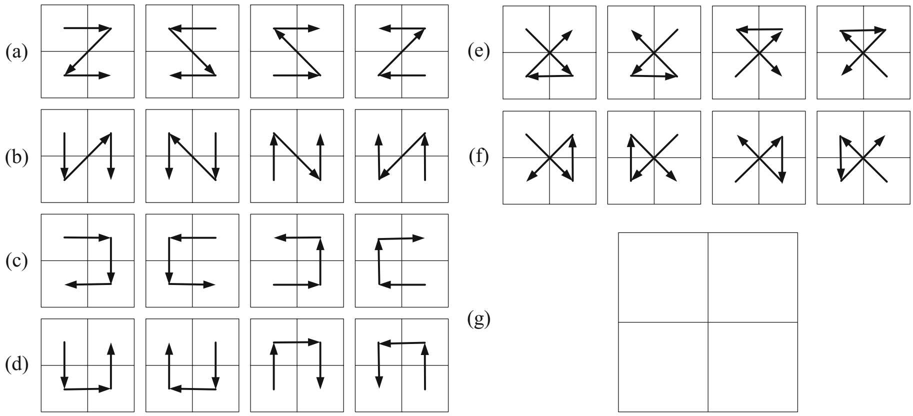


Fig. 2. Patterns of texture direction.

There are connections among pixels of an image, those with the most closely connections are the adjacent pixels, which compose the neighborhood. Image texture can be expressed by the variation of the pixels in neighborhood. Scan the pixels on a 2×2 image block according to the changing of gray value in ascending order, an image block is classified into one kind of patterns in Fig. 2.(a)-(f). If there are equivalent pixels on the image block, define it as non-direction pattern, as shown in Fig. 2.(g). Fig. 3. shows two examples of these patterns. Although the patterns discussed above contain the texture information of an image, we can't realize image retrieval yet. In order to extract the effective texture feature, take a 4×4 image block, which can be divided into four 2×2 subblock in further. A 2×2 subblock forms a neighborhood with the adjacent 2×2 subblock. As there are 7 kinds of patterns, there are 49 kinds of pattern pairs. Record the pattern pairs as $\mathbf{Pair}(j,k)$, define

$$\begin{aligned}&\mathbf{Pat}_i = \mathbf{Pair}(j,k) \quad i = 1,2,\cdots,49;\\ &j = 1,2,\cdots,7; \quad k = 1,2,\cdots,7\end{aligned} \tag{1}$$

Count the number of occurrences of pattern pairs, which is defined as the probabilities of emerged texture direction, namely

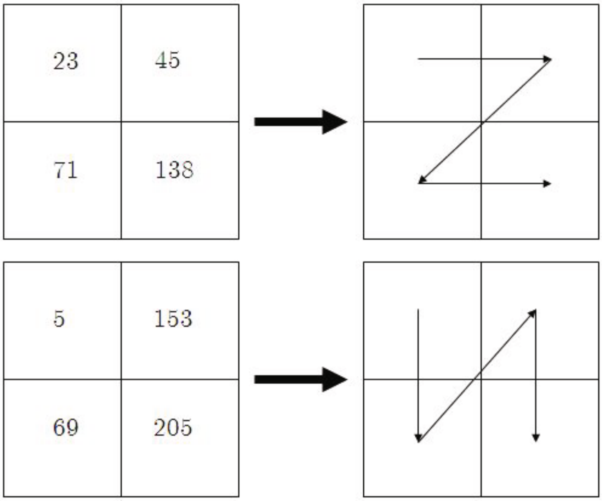


Fig. 3. Pattern examples.

$$\mathbf{Td}_i = \frac{\mathbf{Pat}_i}{\sum_{i=1}^{49} \mathbf{Pat}_i} \quad i = 1, 2, \cdots, 49 \tag{2}$$

Td is the 49-dimension Texture direction descriptor (TDD), which is consisted by $\mathbf{Td}_i,\ i = 1, 2, \cdots, 49$.

TDD is provided with invariance of translation, rotation, zoom, but it just considers the variance of gray direction only, not the variance of gray intensity, so we represent texture intensity by the mean gray value of pattern pairs. When the i_{th} kind of pattern pair appears, record the two image blocks as $G_i(j)$, the texture intensity is defined by the gray intensity of different pattern pairs, namely

$$\mathbf{Ti}_i = \frac{1}{\mathbf{Pat}_i} \sum_{j=1}^{\mathbf{Pat}_i} G_i(j) \quad i = 1, 2, \cdots, 49 \tag{3}$$

In Formula (3), $\mathbf{Pat}_i$ is the number of occurrences of the i_{th} pattern pair. $\mathbf{Ti}_i,\ i = 1, 2, \cdots, 49$ constitutes the 49-dimension texture intensity descriptor (TID) **Ti**.

3 Online Feature Selection

In this section, a method of feature selection with discrimination criterion (FSDC) is presented. The problem that must be tackled in online learning is that how to find out the more representative features. Compared with other machine learning problems, online learning in CBIR system should give out the results at a high rate of speed. In addition, the size of the training set must be small due to the curse of dimensionality. We propose a novel feature selection criterion, which is based on the similarity among different training samples. We just need a small scale of training samples, and the time consumed during training is low, so the proposed method is suitable for online learning in CBIR system.

Denote $F_x = [f_1(x), \cdots, f_k(x), \cdots, f_d(x)]^T$ as the d-dimensional feature vector of image x , the relevant image set is $D = \{x_i^D, i = 1, \cdots, p\}$, and the irrelevant image set is $I = \{x_j^I, j = 1, \cdots, q\}$, the label of relevant images and irrelevant images is $y(x_i^D) = 1$, $y(x_j^I) = -1$ respectively, D_k and I_k represents the projection of D and I along with the k_{th}Cdimensional feature, as given below.

$$\begin{cases} D_k = \{f_k(x_1^D), \cdots, f_k(x_i^D), \cdots, f_k(x_p^D)\} \\ I_k = \{f_k(x_1^I), \cdots, f_k(x_j^I), \cdots, f_k(x_q^I)\} \end{cases} \tag{4}$$

The relation between x and D, I is R_k, U_k respectively, as shown in Formula (5).

$$\begin{cases} R_k = \sum\limits_{i=1}^{p} \left(f_k(x) - f_k(x_i^D)\right)^2, \quad k = 1, 2, \cdots, d \\ U_k = \sum\limits_{j=1}^{q} \left(f_k(x) - f_k(x_j^I)\right)^2, \quad k = 1, 2, \cdots, d \end{cases} \tag{5}$$

The discriminating ability of each feature, otherwise known as the discrimination criterion

$$A_k = R_k/U_k, \quad k = 1, 2, \cdots, d \tag{6}$$

Realign A_k in ascending order as $\widetilde{A}_k$, and select the headmost features according to $\widetilde{A}_k$ of size B. Estimate the category of each sample, as given below.

$$\begin{cases} \widehat{y}(x_i) = 1 if \mathbf{DIF}_i \leq Thr \\ \widehat{y}(x_i) = -1 if \mathbf{DIF}_i > Thr \end{cases} \tag{7}$$

$\mathbf{DIF}_i$ and Thr is given in Formula (8) and (9).

$$\mathbf{DIF}_i = \sum_{k=1}^{B} \left(f_k(x) - f_k(x_i)\right)^2, \quad i = 1, 2, \cdots, p + q \tag{8}$$

$$Thr = \sum_{k=1}^{B} (R_k + U_k)/(p + q) \tag{9}$$

Training error is

$$\phi = \frac{\sum\limits_{i=1}^{p+q} |y(x_i) - \widehat{y}(x_i)|}{(2 * (p + q))} \tag{10}$$

where $y(x_i)$ is the actual category of each training sample $\widehat{y}(x_i)$ is the estimated category of each training sample. The training error of feature subset $S_i, i =$

$1, 2, \cdots, B$ is ϕ^B on the training dataset, select the optimal feature subset by minimizing ϕ^B, the dimension of the optimal feature subset is

$$\widehat{B} = \arg\min_{B} \phi^B \tag{11}$$

the possible value of $\widehat{B}$ is $1, 2, \cdots, d$.

4 Experimental Results

In this section, we evaluate the effectiveness of the proposed feature extraction and feature selection method. First, we describe the image databases. Thereafter, we present the results of an evaluation showing how similar images can be found, and how retrieval precision can be improved visibly.

4.1 Experimental Dataset

For this research, we conduct the experiments on two image databases. The first image database Wang (`http://www.ist.psu.edu/docs/related/shtml`) contains about 11000 images. The second image database Caltech101 (`http://www.vision.caltech.edu/Image_Datasets/Caltech101/`) contains 101 categories of images. The number of images in each category ranges from 33 to 800. By using our feature extraction and selection method, we can select the optimal feature subset that best discriminate among different classes of images, and search the images which are similar to the query.

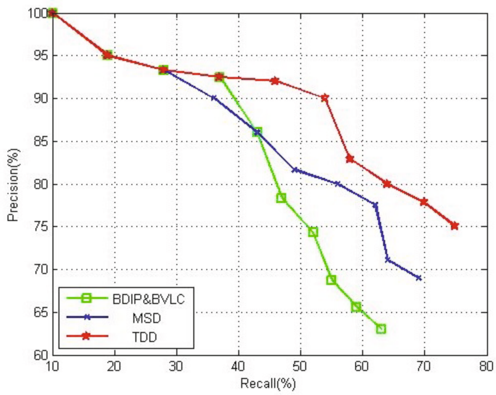
4.2 Recall versus Precision

To evaluate the effectiveness of feature extraction and feature selection method, we compare the proposed method with MSD and BDIP&BVLC on dataset of images Wang and Caltech101. Fig. 4. illustrates two results on image database Wang, and Fig. 5.(a) is the comparison of recall and precision for the three methods, it can be perceived from Fig. 5(a), the proposed method outperforms the

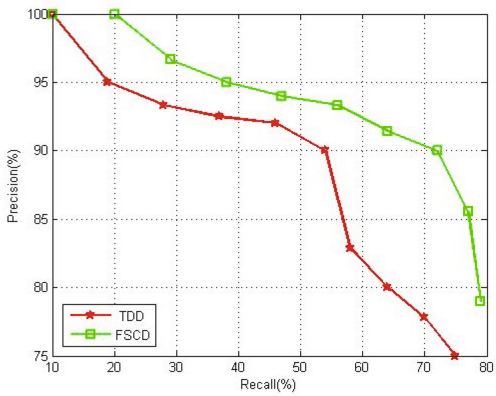
(a) Buses (b) Flowers

Fig. 4. Examples of the results.

other two methods. Texture Direction Descriptor makes up a Dim dimensional feature set with MSD, DCD and EHD, selects a feature subset with Q dimension from the feature set, where $Q = 10, 20, 30, \cdots, Dim$. The feature subset with the highest precision rate is selected as the optimal feature subset. Experimental results show that precision rate reaches the highest when the dimension of feature subset is 80. Fig. 5.(b) is a curve of recall and precision for texture direction feature and proposed online feature selection method, it can be perceived from Fig. 5.(b) that retrieval efficiency is significantly improved after dealing with the proposed online feature selection method.



(a) BDIP&BVLC, MSD and TDD



(b) FSDC and TDD

Fig. 5. Comparison of recall versus precision.

Table 1. ARR and ANMRR

	ARR	ANMRR
BDIP&BVLC	0.8168	0.2132
MSD	0.8436	0.1963
TDD	0.8784	0.1739
FSDC	0.9250	0.1437

4.3 ARR and ANMRR

In order to verify the effectiveness of texture direction feature and online feature selection method in further, we adopt Average Retrieval Rate (ARR) [10] and Average Normalized Modified Retrieval Rank (ANMRR) [10] to evaluate the experimental results on image database Wang and Caltech101. The larger the ARR is, and the smaller the draw a conclusion from Table 1 that the efficiency of texture direction feature is higher than MSD and BDIP&BVLC, and the efficiency is further improved using the proposed online feature selection method.

5 Conclusions

In this paper, a new image feature extraction method is proposed. Then, the proposed texture direction feature constitutes a feature set with other low level visual features. We select the optimal feature subset from the feature set applying a novel discrimination criterion during online feature selection step. The results of the computer simulation experiments on universal databases indicate that the texture direction feature could seek out the relevant images effectively, and the semantic gap is further narrowed by combining online feature selection technology. The proposed texture feature in this paper has translation and scale invariance but not has rotation invariance, we will focus on the rotation invariance in the future work.

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