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Image Retrieval Method based on Integration of Principal Component Analysis and Multiple Features

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Abstract: Existing content-based image retrieval methods exist some drawbacks, such as low retrieval precision, unstable performance. To address these drawbacks, in this paper a content-based image retrieval method is presented based on multi-feature fusion of principal component, oriented-gradient and color histogram. The idea for the proposed method is: firstly, input image is grayscale and flattened into a one-dimensional vector, and the first n principal components from the vector yielded by the PCA algorithm are extracted, in other word, input image is represented as a n×1 dimensional PCA feature vector. Secondly, to remedy color and orientation information missed by PCA, oriented-gradient and color histograms are used to extract orientation and color features respectively. Thirdly, extracted oriented-gradient and color histograms are merged with PCA features to generate the multi-feature representation of the input image. This paper confirms that the proposed multi-feature method can better represent an input image and can easily measure the similarity between images. The experiments are carried out and evaluated based on Corel-1000 , the target method is significantly better than the four popular methods.

Keywords: contented-based image retrieval(CBIR); principal component analysis(PCA); histogram of oriented gradient(HOG); histogram of color(HoC); similarity

1. Introduction

In the past two decades, content-based image retrieval (CBIR) technology has been developed rapidly, and new technologies and methods have emerged in endlessly. As the name implies, CBIR realizes image matching and retrieval based on the inherent features of the image itself. Here, that features of the images generally refer to natural features such as the image color, the texture and the shape. For a given image, the CBIR method pre-extracts the extracted features and is effectively characterized by the extracted features, using such a feature to identify a given image and measure the similarity of the features between the images.

Color feature is one of the basic features of image. Histogram of Color(HoC) [1-2]is the most common representation of image color feature. Because it has feature invariance in terms of geometric changes such as translation, rotation, scaling and so on, it shows good robustness. The texture is another important feature of the image, and it is generally considered that the texture is the regular arrangement combination of the texture elements, and the region with the repeatability, the simple shape and the intensity is regarded as a texture element. Since Dalal et al proposed Histogram Oriented Gradient (HOG) [3-4], HOG has become one of the most important texture feature extraction methods. HOG has been widely used in face recognition, image retrieval and other fields because of its excellent ability to depict local targets.

In recent years, the image retrieval technology based on the combined features has become a hot spot in the research field of CBIR. In 2017, Pavithra et al. [5]proposed a hybrid framework of CBIR, which first uses color moment features for preliminary retrieval, then further uses LBP and Canny to extract texture and edge features and carries out secondary retrieval of preliminary retrieval results. In 2018, Liu et al. [6]proposed a CBIR system based on the fusion of texture features and shape features based on non-downsampling shear transformation and low-order quaternion polar coordinate transformation. In 2019, Pavithra et al.[7]proposed an effective seed point selection method with Dominant Color Descriptor(DCD)which improves the retrieval accuracy of CBIR system based on DCD. In fact, in these methods, different underlying visual features are extracted and combined, but the combination of such features does not always ensure better retrieval accuracy[6] [8].

Since the Eigenface algorithm [9] was proposed last century, the research of face recognition algorithm based on principal component analysis (PCA) [10-12] has been continuing. Chan et al. [13]proposed the PCANet method of applying PCA to CNN, using PCA to learn multi-level filter banks, which accelerates the training speed of neural network, and the accuracy of face recognition reaches the most advanced level at that time. Yao et al. [14] proposed a PCA-based face recognition algorithm, which uses Support Vector Machine (SVM) and Adaptive Boosting as a classifier and has a significant effect. The PCA algorithm is also widely used in the fields of data compression and image compression transmission[15-16].These applications are based on the fact of compression, such a fact shows that the compression process of PCA algorithm is essentially to extract the key feature information of the compressed object, and the PCA principal component is actually a feature representation of the compressed object. At the same time, as a classical compression dimension reduction algorithm, PCA principal component has the advantages of low computational complexity, fast computing speed, strong ability to extract image spatial structure features, which will be verified in section 2.Inspired by this fact, this paper studies a new method different from the traditional CBIR technology. This method is based on the principal component feature extracted by PCA and combines the HOG and HoC as the auxiliary image feature representation. For the convenience of description, it is abbreviated as the PHH method. It is proved that the PHH method is more effective and robust and has higher computational performance than the latest CBIR method.

2. PHH Method

2.1 The Feature Extraction And Feature Representation of PCA

Set as $I_1, I_2, \dots, I_n$ are images taken from the image data set. In order to extract the principal components of the given image I_i and their feature representations, the processing steps are as follows:

(1) The image I_i（$i = 1,2,\cdots,n$）is transformed into a one - dimensional column vector and will be the column(i) of the image matrix P,that is:

$$\mathbf{P} = \left(\mathbf{I}_1^{(1)}, \mathbf{I}_2^{(1)}, \ldots, \mathbf{I}_n^{(1)}\right) \tag{1}$$

Here, Matrix P is $m \times n$, m is the number of pixels of the image I_i and n is the number of amplitudes of the image.

(2) Zero-centering the image set matrix $P = \begin{pmatrix} \boldsymbol{p}_1 \\ \boldsymbol{p}_2 \\ \vdots \\ \boldsymbol{p}_m \end{pmatrix}$, of which $\boldsymbol{p}_j$ is the j-th row of the matrix P, and the zero-center of the j-th row is as follows:

$$\boldsymbol{q}_j = (p_{j1} - \overline{p}_j, p_{j2} - \overline{p}_j, \cdots, p_{jn} - \overline{p}_j) \tag{2}$$

Here p_{jk} is the k-th element of $\boldsymbol{p}_j$ and $\bar{p}_j = \frac{1}{m}\sum_{k=1}^{m} p_{jk}$ is the mean of the k-th line of matrix P. The zero-centered matrix of the image set matrix P is obtained by row zero-center calculation:

$$\mathbf{Q} = \begin{pmatrix} \boldsymbol{q}_1 \\ \boldsymbol{q}_2 \\ \vdots \\ \boldsymbol{q}_n \end{pmatrix}$$

(3) Calculate the eigenvalues of the covariance matrix $C = \frac{1}{m} QQ^T$ of Q and its corresponding eigenvectors, and arrange the n eigenvalues in descending order, take the eigenvectors corresponding to the first k largest eigenvalues and construct the feature matrix $\boldsymbol{F}$ in order.

(4) Transform the zero-cenetred matrix Q into the feature space $\boldsymbol{F}$ to obtain the reduced-dimensional data set $\boldsymbol{P^F}$:

$$\boldsymbol{P^F} = \mathbf{F}^T \mathbf{Q} \tag{3}$$

Each column corresponds to the PCA principal component feature of a particular image in the date set after dimension reduction $\boldsymbol{P^F}$.The PCA principal component feature of image I_i is the column vector i of the matrix $\boldsymbol{P^F}$,recorded as $\boldsymbol{P_i}^{\boldsymbol{F}}$.Conversely,the approximate restored image I_i with PCA feature $\boldsymbol{P_i}^{\boldsymbol{F}}$ can be obtained using PCA feature $\boldsymbol{P_i}^{\boldsymbol{F}}$ and feature matrix $\boldsymbol{F}$,the reduction formula is:

$$\mathbf{I}_i \approx \boldsymbol{F}\boldsymbol{P}_i^{\boldsymbol{F}} \tag{4}$$

For any one of the query images I_{query}, the extraction process of principal components is as follows: