

A Robust Image Retrieval Algorithm Based on Interest points

Wenwen Gao

College Mobile Telecommunications
Chongqing University Of Posts And Telecom
Chongqing, China
Gaowenwen0820@126.com

Yanhong Sun

Library
Chongqing Jiaotong University
Chongqing, China
sunna_9@126.com

Abstract- The global features can not capture all parts of the image having different characteristics and can not contain the spatial features. so in this work we present a novel approach which extracts the local color and texture features based on interest points and utilizes the local information of the interest points to express the contents of images. It not only overcomes the shortage that single image feature can not be truly characterized, but also has a strong robustness to rotation, translation and criterion. Experiment results demonstrate that the proposed approach shows a quite improvement in the retrieval effectiveness.

Keywords- image retrieval, interest points, annular color histogram, texture features, Gabor

I INTRODUCTION

Content-based Image Retrieval (CBIR) becomes a real demand for storage and retrieval of images in digital image libraries and other multimedia datebases. Basically, CBIR aims to search relevant images to a given query image based on the low-level visual contents such as color, texture, shape, and spatial layout.

The global features can not capture all parts of the image having different characteristics and can not contain the spatial features. However, the use of Interest points in content-based image retrieval allows image index based on local properties of image. In this work we extract the local color and texture features based on interest points and utilize the location information of the interest points to express the contents of images. Color features are the most widely used feature[7,9], and can be extracted from images conveniently. Then texture features play an important role in human vision and are important in image classification. Various texture analysis systems and descriptors were proposed over the years. The human visual cortex has separate cells that respond to different frequencies and orientations, which are arguments for multi resolution characterization of the texural images by means of localized filter-bank. This emphasises the efficiency of techniques

such as the Gabor filters, when the end user of the results is a human.

The proposed algorithm in this work combines a few features to retrieve image[11]. It not only overcomes the shortage that a single image features can not be truly characterized, but also has a strong robustness to rotation, translation and criterion. Experiment results show that the algorithm proposed has excellent performance on image retrieval.

II. IMAGE RETRIVAL BASED ON INTEREST POINT

The work firstly utilizes interest points to extract major local information of images. Then combining color and texture of low-level visual contents of using local features at interest points to retrieve, here we use the circular color histogram to extract color features and GABOR wavelet transform to extract texture features to describe the image content. Finally we calculate the similarity between the two images: an query image and an image in the database and output query results according to the similarity. The algorithm flow is illustrated in Figure 1:

A. Interest Points Detection

Interest points are pixels that capture significant local features of an image, and usually locate around corners and edges of images. Hence, the image could be described through the low-level features of the small region around interest points. A good many detectors for interest points have been proposed in the literature[1,2,6,8,10], among which harris corner is one of the most reliable detection techniques.

The harris corner detector is based on the autocorrelation matrix of the image gradients. The autocorrelation matrix $A(x,y,I)$ of an image I at a pixel location (x,y) is given as follows:

$$\hat{A}(x, y, I) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \otimes \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \quad (2-1)$$

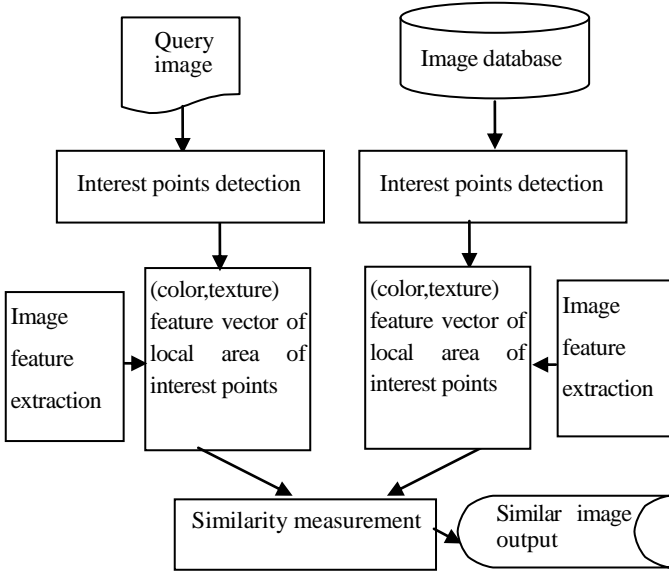


Fig.1 Flowchart of Image retrieval

where $\hat{A}(x, y, I)$ denotes Gaussian partial derivatives of the autocorrelation matrix $A(x, y, I)$; and I_x and I_y calculates the gradients in horizontal and vertical directions, respectively. Instead of explicitly computing the eigenvalues λ_1 and λ_2 of $\hat{A}(x, y, I)$, the following equivalences are used.

$$\det \hat{A}(x, y, I) = \lambda_1 \lambda_2 \quad (2-2)$$

$$\text{trace} \hat{A}(x, y, I) = \lambda_1 + \lambda_2 \quad (2-3)$$

The cornerness response function of the harris corner detector is based on the determinant and trace of the autocorrelation matrix:

$$H_{\text{harris}}(x, y) = \det \hat{A}(x, y, I) - k \left(\text{trace} \hat{A}(x, y, I) \right)^2 \quad (2-4)$$

Where k is a small positive constant that controls the behavior of the $H(x, y)$, for $0.04 \leq k \leq 0.06$. After computing the corner response for all pixels, non maxima suppression is used to get corner points. To check if H is above a certain threshold and to obtain a local maximum in a certain neighborhood, then this point is interest point. The figure 2 illustrates results of interest point sets are extracted by harris detector.

B. Color Feature Description

Although the color histogram is simple to obtain and it is not sensitive to scales, translations and rotations, the global histogram doesn't contain the spatial content of the colors. Here we use an annular histogram to depict the spatial

distribution of colors.

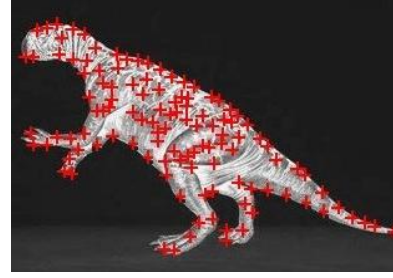


Fig.2 Interest points for the dinosaur image

Firstly we use the perceptive HSV space instead of RGB space, because HSV space is more intuitionistic and more suitable for the features comparing of colors. In HSV color space, Hue is distinguished by different color, such as red, green, blue, which is measured by angle ranged in 0-360; Saturation refers to the concentration of color which is measured by percentage; Value refers to an image's luminance which is measured by percentage as well.

Secondly in this work, the three components H, S, V are quantized in unequal interval respectively, according to human's visual resolving power and subjective perception.

Thirdly following literature[5,7] quantization levels, now the color space is partitioned into $8 \times 3 \times 3 = 72$ color eigenvalues, we construct a 1-dimension vector with H, S and V which would be the column of the annular color histogram. The weight for H will be larger than that of S and V which emphasizes the importance of H in retrieval result.

$$L = HQ_sQ_v + SQ_v + V \quad (2-5)$$

The Q_s and Q_v refer to the quantization levels of S and V, here we set $Q_s = 3$, $Q_v = 3$. thus the formula can be expressed as $L = 9H + 3S + V$.

This way, the weight value can fully capture the image's color information. Moreover, it reduces the influence of an image's luminance. For the one-dimension vector L , it ranges from 0 to 71. Color histogram is created by statistics of the 72 color eigenvalues.

Finally in accordance with the spatial distribution of interest points, we draw N concentric circles. Let w_k is the set of interest points in the k th circle, for $k \in [1, N]$, then the centroid is defined as $C^q = (x^q, y^q)$, where x^q and y^q are defined as follows

$$x^q = \frac{1}{|w_k|} \sum_{x,y \in w_k} x \quad y^q = \frac{1}{|w_k|} \sum_{x,y \in w_k} y \quad (2-6)$$

The radius r^q is defined as

$$r^q = \max_{(x,y) \in w_k} \sqrt{(x - x^q)^2 + (y - y^q)^2} \quad (2-7)$$

Then annular color histogramms are calculated in each annular region. Let $H_k = \{h_{k,i} | 0 \leq i \leq 71\}$, for

$k \in [1, N]$, where $\forall (x, y) \in w_k, (x', y') \in \delta((x, y), a)$

and $h_{k,i} = \text{sum}\{p(x', y') | p(x', y') = i\}$ for i is color value and a is the radius of neighborhood of interest points

C. Texture Feature Description

Gabor wavelets[7] are widely adopted to extract texture features from the images for image retrieval, because they best accord with the vision mechanism of human being which is non-symmetrical and non-linear in observing image. Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and a specific direction. Expanding a signal using this basis provides a localized frequency description, therefore capturing local features of the signal. Texture features can be extracted from this group of energy distributions. The scale and orientation tunable property of gabor filters make it especially useful for texture analysis.

Gabor elementary functions are Gaussians modulated by complex Sinsoids.

$$g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right) + 2\pi jwx\right] \quad (2-8)$$

With $g(x, y)$ as the mother wavelet, through its appropriate scale and selection transformation, we can obtain a set of self-similar filters known as Gabor waveler.

$$g_{mn}(x, y) = a^{-m} g(x', y'), a < 1, m, n \in Z \quad (2-9)$$

$$\begin{aligned} \text{Where } x' &= a^{-m}(x \cos \theta + y \sin \theta) \\ y' &= a^{-m}(-x \sin \theta + y \cos \theta) \quad \theta = n\pi/k, \end{aligned}$$

By changing the value of m and n , we can obtain a set of filters family with different directions and scales. For a given Image $I(x, y)$ with size $P \times Q$, its discrete Gabor wavelet transform is given by

$$G_{mn}(x, y) = I(x, y) \times g_{mn}(x, y). \quad (2-10)$$

After applying Gabor filter on the image with different orientation at different scale, we obtain an array of magnitudes which represent the energy content at different scale and orientation of the image.

$$E(m, n) = \sum_{x=0}^P \sum_{y=0}^Q |G_{mn}(x, y)| \quad (2-11)$$

The main purpose of texture based retrieval is to find images or regions with similar texture therefore the following mean μ_{mn} and standard deviation σ_{mn} of the magnitude of the homogenous texture feature of the region.

$$\mu_{mn} = \frac{E(m, n)}{P \times Q} \quad (2-12)$$

$$\sigma_{mn} = \sqrt{\frac{\sum_{x=0}^P \sum_{y=0}^Q (|G_{mn}(x, y)| - \mu_{mn})^2}{P \times Q}} \quad (2-13)$$

A feature vector for texture representation is created using μ_{mn} and σ_{mn} as the feature component. The feature vectors for m scales and n orientations are given by $f(\mu_{00}, \sigma_{00}; \mu_{01}, \sigma_{01}; \dots; \mu_{mn}, \sigma_{mn})$

In this experiment, we have chosen 4 scales and 8 orientations.

D. Similarity Measure

In the retrieval, target images are ranked in descending order of similarity to the query image by the distance between the combined feature vector of the query image and that of the target image. Let Q and I be a query image and target images. The similarity between the two images is given by

$$S(Q, I) = \omega_c S_{color}(Q, I) + \omega_t S_{texture}(Q, I) \quad (2-14)$$

Where ω_c and ω_t are two weight coefficients, $\omega_c + \omega_t = 1$. In the following experiment, the two coefficients are regarded as 0.5. $S_{color}(Q, I)$ and $S_{texture}(Q, I)$ represent the color similarity and the texture similarity between two images respectively. We employ histogram sequence as the color similarity metric, which is defined as

$$S_{color}(Q, I) = \sum_{k=1}^N \frac{\omega_k}{N_p} \sum_{l=1}^L \min(H_l(Q), H_l(I)) \quad (2-15)$$

Where ω_k denotes the number of the interest points in the k^{th} annular region. The Gauss function is used to test the similarity of spatial feature.

The texture similarity is defined as

$$S_{texture}(Q, I) = norm(\sqrt{\sum_{i=1}^n |f_{Qi} - f_{Ii}|^2}) \quad (2-16)$$

■ III. RETRIEVAL EXPERIMENTS RESULT

In this work, experiments have been conducted for an image database containing 1000 images, which are collected from the COREL database. These images belong to 10 categories involving beach, buildings, buses, dinosaurs, flowers and so on. Each category includes 100 images. A retrieval result performed by our method is showed in Figure 4. The top-left image is a query image presented by the user. The system outputs the query results according to the similarity order from left to right and top to bottom.

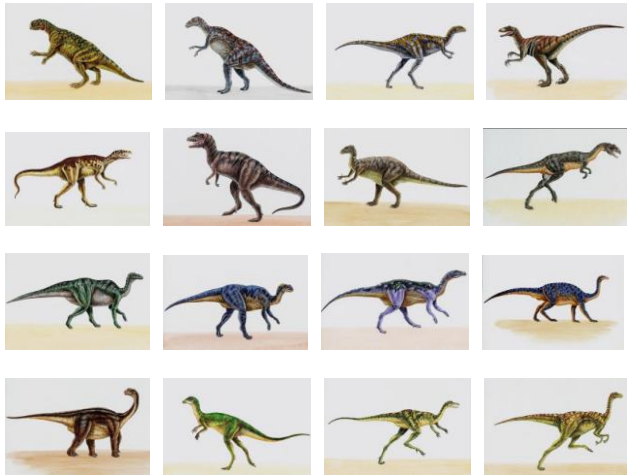


Fig.3 Retrieval result of our method

In order to verify the performance of our method, we also implement the methods of the literature[4,6] under the same software and hardware conditions. Retrieval precision is used to estimate the effectiveness of our retrieval method. The precision is computed by

$$\text{Precision} = n/T.$$

Where T is the number of images returned by the retrieval system and n is the number of output related images. Taking out 10 images randomly as query images from each category, we record the precision for 20 test images, and compute the average of them. Figure 5 shows precision curves of different methods. We can see that our proposed method is superior to the literature[4,6], and improves the average retrieval precision by 8.07 percent and 14.9 percent

compared with the literature[4,6], respectively. Where numbers are 1,2,3,...10, corresponding categories are Beach, Buildings, Buses, Dinosaurs, Flowers, Horse, Mountain, Food, respectively.

The future work is how to add relevance feedback to this algorithm. In order to enhance retrieval precision of images.

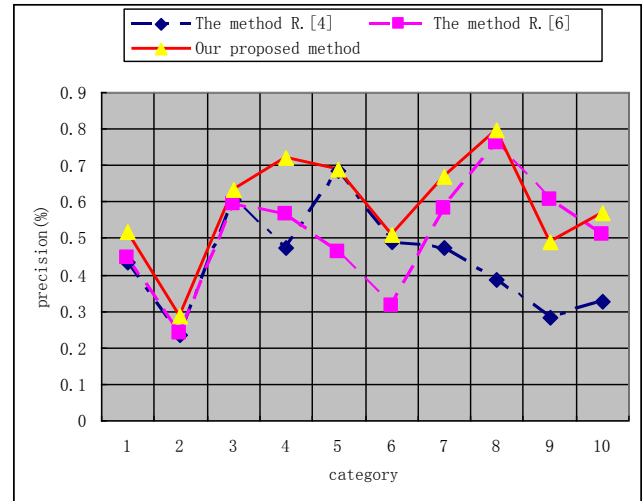


Fig.4 Precision curves of different methods

REFERENCE

- [1] C.Harris and M.J.Stephens. "A combined corner and edge detector". In Proc.Alvery Vision Conference, PP.147-152,1998.
- [2] S.Bres and R. Schettimi. "Detection of interest points for image indexation". IEEE Conference on image Processing, New York, pp427-434,1999.
- [3] Quanming Zhou, Guohua Geng. "Content-based Image Retrieval Technology." Tsinghua University publishing house, July 2007.
- [4] ZENG Zhi-Yong, AN Zhi-Yong, ZHOU Li-Hua. "A Novel Image Retrieval Algorithm Based on Color and Distribution Entropy of Prominent Interest Points". Journal of Infrared Technology pp.160-163, Mar. 2007.
- [5] Cao lihua, Liu Wei, Li Guohui. "Research and implementation of an image retrieval algorithm based on multiple dominant colors". Journal of Computer Research and development, vol.36, pp.96-100, Jan 1999.
- [6] Meng Fan-jie, Guo Bao-long. "A novel image retrieval algorithm based on the color and distribution of interest points". Journal of xi'dian University, vol 32, pp. 256-259, Feb 2005.
- [7] Ping Yu, Cheng Zhang, ChunHua Du. "Image retrievals based in color and texture features". IEEE Conference on image Processing , pp. 1 – 4, 2007.
- [8] Hoang Ng-Duc et al. "Image retrieval using contourlet based interest points". 10th International Conference on Information Science, pp.93-96, 2010.
- [9] J.Stoetinger, A.Hanbury, N.Sebe and T. Gevers. "Do color interest points improve image retrieval?". IEEE Conference on image Processing, pp.169-172, 2007.
- [10] Mohammed Qatran , Khaled Mahar and Ossama Ismail. "Interest Points Matching System Based On Non-Subsampled Contourlet Transform" 2010 2nd International Conference on Computer Technology and Development, pp.245-249. 2010.
- [11] Weijun Dong, Mingquan Zhou, Guohua Geng. "Image retrieval technique based on combined features". Journal of Compute Applications and Software. 2005, 22(11):34-36.