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Non Linear Transform for Retrieval System in Consideration of Feature Combination Technique

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Abstract

An flexible and effective image retrieval system using weighted combination of image retrieval features, is proposed. The proposed method properties such as, shape an textural features are quite simple to derive and effective, and can be extracted in real time. In retrieval systems the common method of improving retrieval performance is by weighting the feature vectors. In this paper a new and reliable method of improving retrieval performance, and which complement feature weighting is proposed. Based on results obtained from this paper, we hereby state that the key to a breakthrough in current research in semantic image retrieval lies in the use of wavelet texture feature. As simulation results show that the presented method is so efficient to other compared methods.

Keywords: *feature, extraction, retrieval, wavelet*

INTRODUCTION

An active research area that is in the heart of all the search engine systems is the extraction and retrieval of images from a database given a query [1]. An image retrieval system is a system for searching and retrieving images from a large database of digital images. The most common method of image retrieval utilizes some method of annotation such as keywords, or descriptions to the images so that retrieval can be performed over the labels. Unfortunately manual annotation is time-consuming and expensive [2]. The answer to the previous difficulty is termed Content based image Retrieval (CBIR) CBIR describes the process of retrieving desired images from the image database on the basis of syntactical image features. Most current CBIR techniques are geared towards retrieval by some aspect of image appearance, depending on the automatic extraction and comparison of image features judged most likely to convey that appearance[3]. The features most often used include color, texture, shape, spatial information and multi-resolution pixel intensity transformations such as wavelets or multi-scale Gaussian filtering. Its benefits of Fourier as well as local analysis of images enables analysis of gradual changes of texture and texture variations which are essential properties of real-world scenes. In CBIR systems the common method of improving retrieval performance is by weighting the feature vectors. In this paper a new and reliable method of improving retrieval performance, and which complement feature weighting is proposed. The system is comprehensive because it incorporates Wavelet filters of different grid sizes and flexible because the feature weights can be adjusted to achieve retrieval refinement according to user's need and robust because the system's algorithm is applicable to retrieval in all kinds of image database. In this paper, textural features derived from six grid sizes of independent and different Wavelet filter banks were incorporated into the CBIR system by taking advantage of the fact that each grid size of filter is suited to capture particular set of localized frequency-images in diverse database. This design enable the Wavelet filter to optimally cover the frequency space, and gives the system the artificial intelligence to 'scroll' locally and globally through the database and retrieve images based on high level features. It is shown that Wavelet filters can replay their efficient texture feature extraction in pure texture images, in complex and real-world images, because these images, though constituted by constant grey levels, the various constant grey levels within the global image constitute texture that can be captured by the tuneable characteristics of Wavelet filters. The rest of paper is organized for feature extraction and simulation results and the last part of manuscript for conclusion.

Feature Extraction

Textural Features

Textures are the visual patterns in an image that have properties of homogeneity that do not result from the presence of only a single color or intensity. Today, the most commonly used methods for texture feature description are statistical and transform based methods. In the present work a transformed based method is used. The state-of-the-art in transformed based texture feature extraction uses Wavelet wavelets. This is due to physiological research evidence that Wavelet filters model the neurons in the visual cortex of the human visual system. Furthermore, showed that Wavelet features performs better than using pyramid structured, tree-structured wavelet transform features and multi-resolution simultaneous autoregressive model. A total of twenty four wavelets were generated from the "mother" Wavelet function using four scales of frequency and six orientations. Redundancy, which is the consequence of the nonorthogonality of wavelets, was addressed by choosing the parameters of the filter bank to be set of frequencies and orientations that cover the entire spatial frequency space so as to capture texture information as much as possible. The lower and upper frequencies of the filters were set at 0.04 octaves and 0.5 octaves respectively, the orientations were at intervals of 30 degrees, and the half-peak magnitudes of the filter responses in the frequency spectrum are constrained to touch each other. Each image I (x, y) in the database is convolved with each wavelet in the filter bank according to the convolution equation $G_{mn}(x,y) = \int I(x-s, y-t)\bar{\phi}(s,t)$ where s and t are the dimensions of the filter and is the complex conjugate of the Wavelet. Furthermore, m $\{1,2,3,4\}$, n $\{1,2,\ldots,6\}$ correspond to the scales of frequency and orientations respectively. By assuming spatial homogeneity of texture regions the mean and the std. deviation of the magnitude of the transformed coefficients was computed according to:

$$\mu_{mn} = \int \left| G_{mn}(x,y) \right| dxdy \tag{1}$$

$$\sigma_{mn} = \sqrt{\int \left(G_{mn}(x,y) - \mu_{mn} \right)^2 dxdy} \tag{2}$$

Finally, the texture feature vector for each image is constructed using the computed values for the mean and std. deviation according to:

$$I_{fr}(x,y) = [\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots, \mu_{35}\sigma_{35}]$$

Shape Feature

Shape of an object is the characteristic surface configuration as represented by the outline or contour. Shape recognition is one of the modes through which human perception of the environment is executed. Shape is important in CBIR systems because it corresponds to region of interests in images. In CBIR system designed for specific domain such as trademarks and silhouettes of tools, shape segmentation can be automatic and effective. However this is not the case for a system having heterogeneous database. In this case shape segmentation may be difficult or sometimes impossible. In our proposal the shape features are extracted using local mean and std. deviation in a search 5 × 5 neighborhood employing the following formulas:

$$\mu_I(x,y) = \sum_{g=-2\&h=-2}^{2} I(x-g, y-h) \times Z(5,5) \tag{3}$$

$$\sigma_I(x,y) = \sum_{g=-2\&h=-2}^{2} I(x-g, y-h) \times K(5,5) \tag{4}$$

where Z and K are the impulse responses of the mean and std. deviation filters respectively. For that, each image in the database passes through a 5 × 5 grid size Wavelet filter bank. Twenty four output images are then obtained. Afterwards, similarly to the pre-filtered image the local mean and std. deviation of each output of the filter bank is also calculated using a 5×5 neighborhood according to:

$$\mu_{pmn}(x,y) = \sum_{g=-2\&h=-2}^{2} G_{pmn}(x-g, y-h) \times Z(5,5) \tag{5}$$

$$\sigma_{pmn}(x,y) = \sum_{g=-2\&h=-2}^{2} G_{pmn}(x-g, y-h) \times K(5,5) \tag{6}$$

Thus for each pixel in the image there are twenty four reference pixels. Consider the pixel in the image and the twenty four corresponding pixels in the output of the filter bank, the distance between the image feature vector and any of the corresponding pixels feature vector is computed as:

$$D_{pmn}(x,y) = \left| \mu_{pmn} - \mu_I \right| + \left| \sigma_{pmn} - \sigma_I \right| \tag{7}$$

EXPERIMENT RESULT

The proposed CBIR system was tested using the test database of wang image database that consists of 800 images. The images are manually annotated in 110 categories. The performance of the proposed system is assessed using recallprecision curves with the help of randomly selected query-images. Recall is defined as the fraction of relevant objects that are retrieved whereas precision is the fraction of retrieved objects that are relevant to the query. In the case under consideration the relevance or not of an image to a query-image is assessed using the annotation assigned to each individual image. Implementing a CBIR system is a painstaking process. The reason is that the Wavelet filter dictionary adopted for the system design indicates

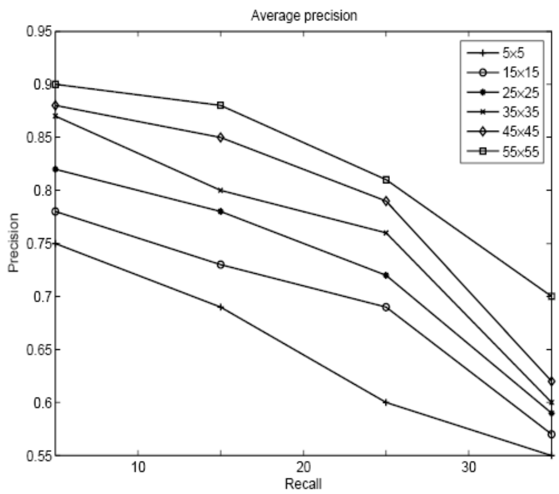

Fig.1. The average precision of the CBIR system, using all features.

the frequency of operation and the number of filters for optimal performance but it does not have a readymade answer for the filter grid size that gives optimal performance. On that, it is generally acceptable that larger Wavelet grids are capable of capturing slowly varying levels than a lower grid size filter. Therefore, this aspect has been taken care by computing texture feature of the images in the database using Wavelet filters of grid sizes 5×5, 15 × 15, 25 × 25, 35 × 35, 45 × 45 and 55 × 55. In assessing the performance of the proposed system a series of query-images are given to the system and then one precision curve is computed per query. Afterwards all the curves are averaged and this yields the so-called average recall precision curve. Fig. 1 depicts the average curves when all features are utilized. In the case of Fig. 1 the weights are 0.7, 0.15 and 0.15 respectively.

CONCLUSION

An simple, robust, flexible and effective image retrieval system using weighted combination of Wavelet texture features and shape features is hereby proposed. The shape and textural features are quite simple to derive and effective, and can be extracted in real time. The system is flexible because the feature weights can be adjusted to achieve retrieval refinement according to user's need. It is robust because the system's algorithm is applicable to retrieval in virtually all kinds of image database. In this paper a new and reliable method of improving retrieval performance, and which complement feature weighting is proposed. Since the system use Wavelet filter for texture feature extraction, the proposal is weighting the features of the system as derived from various sizes of Wavelet filter. The system has lots of superiority to other compared systems such as high percentage of retrieval and fast retrieval process.

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