Content Based Image Retrieval Using Independent Component Analysis

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Summary
Content Based Image Retrieval (CBIR) has become one of the most active research areas in the past few years. Many indexing techniques are based on global features distribution such as Gabor Wavelets. [1]. In this paper we present a new approach for global feature extraction using an emerging technique known as Independent Component Analysis (ICA). A comparative study is done between ICA feature vectors and Gabor feature vectors for 180 different texture and natural images in a databank. Result analysis show that extracting color and texture information by ICA provides significantly improved results in terms of retrieval accuracy, computational complexity and storage space of feature vectors as compared to Gabor approaches.

Key words:
CBIR, Gabor Wavelets, ICA, Similarity measurements

1. Introduction

Recent years have witnessed a rapid increase of the volume of digital image collection, which motivates the research of CBIR. To avoid manual annotation many alternative approaches were introduced by which images would be indexed by their visual contents such as color, texture, shape etc. Many research efforts have been made to extract these low level image features, evaluate distance metrics and look for efficient searching schemes.

A CBIR is a two step approach to search the image in database. First, for each image in the database, a feature vector is computed and stored in feature database. Second given a query image, its feature vector is compared to the feature vectors in the data base and images most similar to the query image are returned to the user. The feature and similarity measure used to compare two feature vectors should be efficient enough to match similar images.

We have presented ICA of images as a computational technique for creating a new data dependent filter bank. The new ICA filter bank is similar to the Gabor filter bank but it seems to be richer in the sense that some filters have more complex frequency responses. They are able to capture the inherent properties of textured images. The ICA based approached is different from existing filtering methods in that it produces a data dependent filter bank.[6]
This paper describes an image retrieval technique based on ICA and the results are compared with the Gabor features. We demonstrate our retrieval results both for texture images and for natural images.

The paper is organized as follows: Section 2 describes fundamentals of 2-D Gabor filters. Section 3 describes ICA. Section 4 discusses similarity measurement techniques used for retrieval. In section 5, we present experimental results of image retrieval based on Gabor as well as ICA feature vector. Section 6 concludes the paper.

2. Gabor Filter Wavelets

Gabor wavelet is widely adopted to extract texture features from the images for retrieval and has been shown to be very efficient [9,11]. Basically Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and specific orientation. The scale and orientation tunable property of Gabor filter makes its especially useful for texture analysis. The design of Gabor filter is done as follows:

Gabor Filter (wavelet)[8]
For a given image I(x,y) with size PXQ, its discrete Gabor wavelet transform is given by a convolution:

$$G_{mn}(x,y)=\sum_{s}\sum_{t} I(x-s,y-t)\psi^{*}_{mn}(s,t) \quad (1)$$

where, s and t are the filter mask size variables, and ψ^{*}_{mn} is a complex conjugate of ψ_{mn} which is a class of

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self-similar functions generated from dilation and rotation of the following mother wavelet:

$$\psi(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp[-\frac{1}{2}(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2})].\exp(j2\pi Wx) \quad (2)$$

where W is called the modulation frequency. The self-similar Gabor wavelets are obtained through the generating function:

$$\psi_{mn}(x,y)=a^{-m}\psi(\tilde{x},\tilde{y}) \quad (3)$$

where m and n specify the scale and orientation of the wavelet respectively, with m=0,1,…,M-1, n=0,1,…..N-1, and

$$\tilde{x}=a^{-m}(x\cos\theta+y\sin\theta) \quad (4)$$
$$\tilde{y}=a^{-m}(-x\sin\theta+y\cos\theta)$$

where $a>1$ and $\theta=n\pi/N$.

The variables in the above equation are defined as follows:

$$a=(U_h/U_l)^{\frac{1}{M-1}},$$
$$W_{m,n}=a^mU_l \quad (5)$$

$$\sigma_{x,m,n}=\frac{(a+1)\sqrt{2\ln 2}}{2\pi a^m(a-1)U_l},$$
$$\sigma_{y,m,n}=\frac{1}{2\pi\tan(\frac{\pi}{2N})\sqrt{\frac{U_h^2}{2\ln 2}-(\frac{1}{2\pi\sigma_{x,m,n}})^2}} \quad (6)$$

In our implementation, we used the following constants as commonly used in the literature:

U_l =0.05, U_h =0.4,

s and t range from 0 to 60, i.e., filter mask size is 60 x 60.

3. Independent Component Analysis

In the literature there are three different basic definition of **ICA [1],** here we are using the basic definition that, ICA of the random vector X consists of finding a linear transform

$$X=AS \quad (7)$$

So that the components $\mathbf{S}_i$ are as independent as possible, with respect to some maximum function that measures independence. This definition is known as general definition where no-assumptions on the data are made [1,2].

A much faster method for finding the ICA is using a fixed-point algorithm. Fast ICA is based on a fixed-point iteration scheme for finding a maximum of the non-guassianity of $\mathbf{W^TZ}$, where **W** is the random matrix to be trained for finding ICA and **Z** is the whiten known mixed matrix**.** It can be derived as an approximate Newton iteration. The fast ICA algorithm using negentropy combines the superior algorithmic properties resulting from the fixed-point iteration with the preferable statistical properties due to negentropy. Prior to the application of the algorithm we have to do certain preprocessing in order to make data statistical independent.

1. Center the data to make its mean zero.
2. Choose m, the number of independent components to estimate from the PCA.
3.. Whiten the data to give **Z**.
4. Choose the random mixing matrix **W**
5. Orthogonalized the matrix W
6. Let $\mathbf{W_1 \leftarrow E\{Zg(W^TZ)\} - E\{g'(\ ^TZ)\}W}$,
   where g is defined as
   g(y)= tanh(y) or
   $g(y)=y^3$
7 Orthogonalized matrix **W**
8. If not converged, go back to step 6.
9. Let $\mathbf{W}_2 \leftarrow \mathbf{W}_1/||\mathbf{W}_1||$
10. for second ICA go to step 6
11. Repeat for i= 1,2,3….m

The filter bank consists of the ICA image basis **w** learned from the images, which are statistically independent. We use these basis images to capture the inherent structure of the texture. The ICA basis functions are data dependent in the sense that they are learned from the training data at hand and they will be different for different training data.

4. Similarity Measurements And Retrieval

Texture is an important feature of natural image. A variety of techniques have been developed for measuring texture similarity. Most of the techniques rely on computing values of second order statistics calculated from the query and stored images [8,11]. In this section, we describe texture similarity calculation . Let

$$E(m,n)=\sum_x\sum_y|F_{mn}(x,y)|, \quad (8)$$

m=0, 1,…, M-1; n=0, 1,…,N-1

These magnitudes represent the energy content at different scale and orientation related to Gabor filters and Independent Components of the image.

The main purpose of texture-based retrieval is to find images or regions with similar texture. It is assumed that we are interested in images or regions that have homogenous texture, therefore the following mean μ_{mn} and standard deviation σ_{mn} of the magnitude of the transformed coefficients are used to represent the homogenous texture features of the region:

$$\mu_{mn} = \frac{E(m,n)}{P \times Q} \qquad (9)$$

$$\sigma_{mn} = \sqrt{\frac{\sum_x \sum_y (|G_{mn}(x,y)| - \mu_{mn})^2}{P \times Q}} \qquad (10)$$

A feature vector f (texture representation) is created using μ_{mn} and σ_{mn} as the feature components. Five scales and 6 orientations are used in common implementation and the feature vector is given by:

$$f = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots\ldots\ldots \mu_{56}, \sigma_{56}). \qquad (11)$$

The texture similarity measurement of a query image Q and the target image T in the database is defined by:

$$D(Q,T) = \sum_m \sum_n d_{mn}(Q,T) \qquad (12)$$

where

$$d_{mn} = \sqrt{(\mu_{mn}^Q - \mu_{mn}^T)^2 + (\sigma_{mn}^Q - \sigma_{mn}^T)^2} \qquad (13)$$

5. Experimental Results

We design a Gabor wavelet for 5 scales and 6 orientations. We have conducted retrieval test both on texture images and natural images. The data is composed of 18 different kind of images such as tulip, texture, satellite image, animal, airplane, flag, natural images etc. There are 10 images of every kind which means there are total 180 images in a databank.

The retrieve results are show for the flag as the query image.

Fig.1(a) Flag retrieve Using ICA

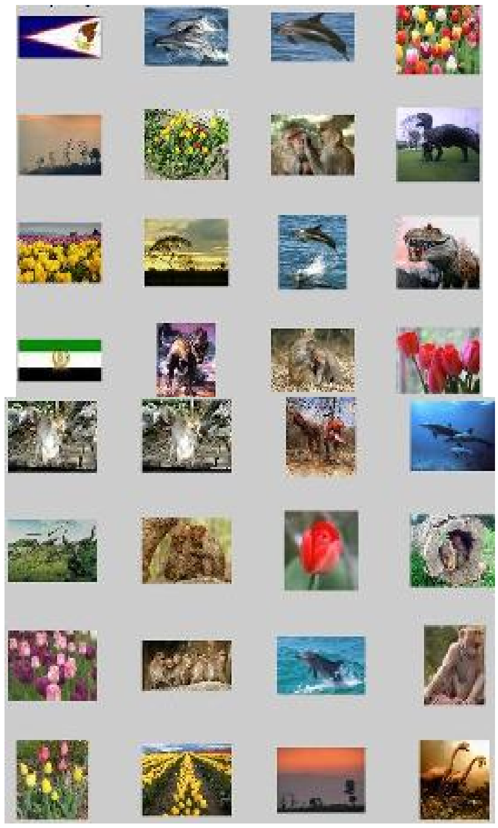

Fig. 1(b). Flag retrieve using Gabor

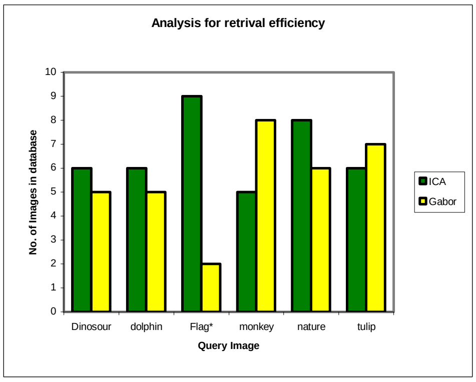

Fig.2(a)

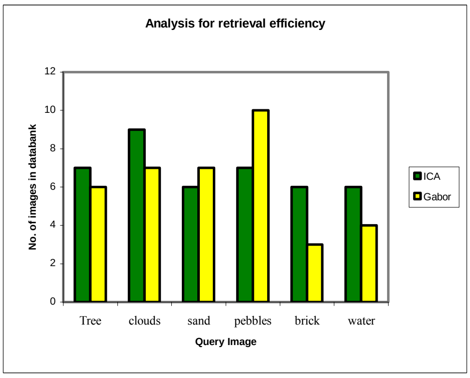

Fig.2(b).

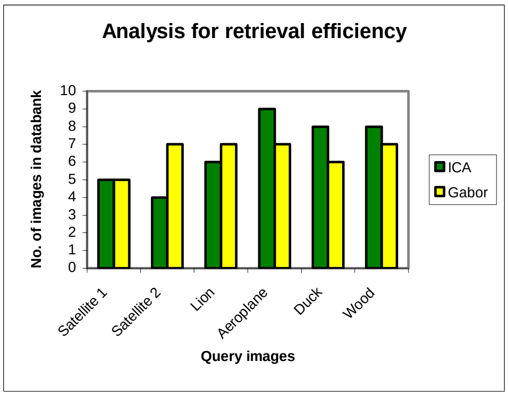

Fig.2(c).

Fig.2. Analysis for retrieval efficiency

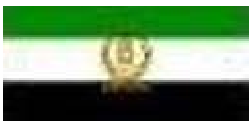

Fig.3 (a). Flag as Query

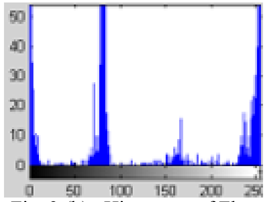

Fig. 3 (b). Histogram of Flag

Fig. 4 (a). Brick as query

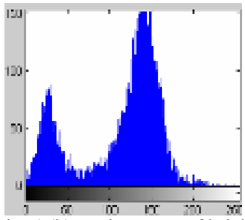

Fig. 4 (b). Histogram of brick

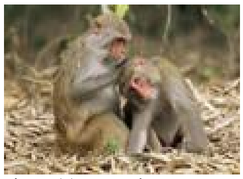

Fig. 5 (a). Monkey as query

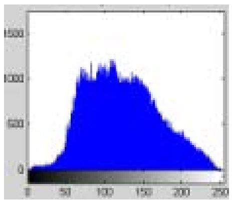

Fig. 5 (b). Histogram of Monkey

Fig. 6 (a). Satellite 2 as Query

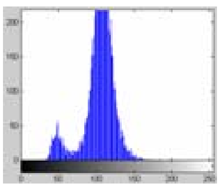

Fig. 6 (b). Histogram of Satellite 2

Query	ICA	Gabor
Flag	**9**	2
Brick	**6**	3
Monkey	5	**8**
Satellite2	4	**7**

Table 1: No. of images retrieve out of 10 images in databank in first 32 retrieve images

The first 32 retrieve images using ICA and Gabor are shown in Fig. 1(a) and Fig. 1(b) respectively for illustration. The retrieve images are ranked in the decreasing order based on the similarity of their features to those of the query image. Fig 2 shows the comparative analysis for retrieval efficiency for all the 18 queries. Table 1 gives the number .of images retrieve out of 10 images in databank in first 32 retrieve images. For illustration we provide the 4 query images where we found some interesting results with respect to their histogram. Fig.3. 4, 5, and 6 shows the above said query images along with their histogram. If we compare the analysis of the retrieval efficiency with the histogram of the query image it can be seen that the histogram which is having a single peak with nearly Gaussian distribution can be retrieve very efficiently by Gabor filters (Fig. 5 and 6), whereas the histogram which is having non Gaussian distribution can be retrieve very efficiently using ICA filters (Fig. 3 and 4). We found that these results are mostly true for other query images also.

6. Conclusion

We have presented ICA of textures and natural images as a computational technique for creating a new data dependent filter bank. The new ICA filter bank is similar to the Gabor filter bank, but it seems to be richer in the sense that some filters have more complex frequency responses. Except, for certain distribution of pixels with gray scale or histogram, where either ICA or Gabor works very well. Our experiments using multi-textured images shows that the ICA filter bank yield similar or better results than the Gabor Filter bank.

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