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 filters to have more complex frequency responses. They are able to capture the inherent properties of textured images. The ICA based approach 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 \( \psi^{*}_{mn} \) is a complex conjugate of \( \psi_{mn} \) which is a class of
self-similar functions generated from dilation and rotation of the following mother wavelet:

\[ \psi(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left(-\frac{x^2}{2\sigma_x^2} - \frac{y^2}{2\sigma_y^2}\right) \exp\left(j2\pi f_0x\right) \]

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

\[ \psi_{mn}(x, y) = a^{-m} \psi(\tilde{x}, \tilde{y}) \]

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

\[ \tilde{x} = a^{-n} (x \cos \theta + y \sin \theta) \]
\[ \tilde{y} = a^{-m} (-x \sin \theta + y \cos \theta) \]

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

The variables in the above equation are defined as follows:

\[ a = \left(\frac{U_h}{U_l}\right)^{\frac{1}{2m-1}} \]
\[ W_{m,n} = a^m U_l \]

\[ \sigma_{x,m,n} = \frac{(a + 1)\sqrt{2\ln 2}}{2\pi a^n(a - 1)U_l} \]
\[ \sigma_{y,m,n} = \frac{1}{2\pi \tan\left(\frac{\pi}{2N}\right) \sqrt{\frac{U_l^2}{2\ln 2} - \frac{1}{2\pi \sigma_{x,m,n}}}} \]

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 definitions of ICA [1], here we are using the basic definition that, ICA of the random vector \( X \) consists of finding a linear transform

\[ X = AS \]

So that the components \( S \) 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-gaussianity of \( W^T Z \), where \( W \) is the random matrix to be trained for finding ICA and \( Z \) is the whitened 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 \( W_1 \rightarrow E\{Zg(W^T Z)\} - E\{g'(Z)\}W \) where \( g \) is defined as

\[ g(y) = \tanh(y) \text{ or } g(y) = y^3 \]

7. Orthogonalized matrix \( W \).
8. If not converged, go back to step 6.
9. Let \( W_2 \leftarrow W_1/||W_1|| \).
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

\[ E(m, n) = \sum_{x} \sum_{y} |F_{mn}(x, y)| \]

\( m = 0, 1, ..., M-1 \); \( n = 0, 1, ..., N-1 \)

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 \( \mu_{mn} \) and standard deviation \( \sigma_{mn} \) of the magnitude of the
transformed coefficients are used to represent the homogenous texture features of the region:

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

$$\sigma_{mn} = \sqrt{\sum_{x} \sum_{y} (|G_{mn}(x,y)| - \mu_{mn})^2}$$ \quad (10)

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

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

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

$$D(Q,T) = \sum_{m} \sum_{n} d_{mn}(Q,T)$$ \quad (12)

where

$$d_{mn} = \left((\mu_{mn}^Q - \mu_{mn}^T)^2 + (\sigma_{mn}^Q - \sigma_{mn}^T)^2\right)$$ \quad (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
Analysis for retrieval efficiency

Fig. 2(a).

Analysis for retrieval efficiency

Fig. 2(b).

Analysis for retrieval efficiency

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
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.

References

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<thead>
<tr>
<th>Query</th>
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<th>Gabor</th>
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<tbody>
<tr>
<td>Flag</td>
<td>9</td>
<td>2</td>
</tr>
<tr>
<td>Brick</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>Monkey</td>
<td>5</td>
<td>8</td>
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<tr>
<td>Satellite2</td>
<td>4</td>
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Table 1: No. of images retrieve out of 10 images in databank in first 32 retrieve images
Computer Picture processing which has subsequently won him and his group a NRDC Award.

Dr. Deekshatulu was Head, Technical Division, NRSA in April 1976 and became Director in January 1982, promoted to the grade “Outstanding Scientist” in July 1989 and “DISTINGUISHED SCIENTIST” (grade of Secretary) in July 1995 and retired from NRSA in October 1996. He has over 130 research publications to his credit. He has guided 12 Ph.D. Scholars and over 50 M.Tech. students' dissertations. His current interests are Remote Sensing Data Analysis, Digital Image Processing and Neural Networks.

He is FELLOW IEEE (USA), Fellow IETE, Fellow Indian Society of Remote Sensing (ISRS), Fellow Computer Society of India (CSI), Life Member Biomedical Engineering Society of India, Life Member of Indian Physics Association (IPA), Life Fellow of Indian Academy of Medical Physics. Fellow Indian National Cartographic Association (INCA), Life Member Instrument Society of India, Life Member System Society of India and Fellow THIRD WORLD ACADEMY OF SCIENCES (ITALY).


Dr. Deekshatulu was a UN / FAO consultant in Beijing during November, 1981. He was the Government representative in the UN/ESCAP/RSSP Directors' meetings and Intergovernmental Consultative Committee meetings from 1985-95. He was a UN/ESCAP Senior Consultant during September-November, 1996. He has about 15 years teaching/research experience and 30 years of technical/administrative experience. He was Director of Centre for Space Science and Technology Education in Asia and the Pacific (CSSTE-AP), Affiliated to the United Nations, IIRS Campus, Dehra Dun, India from November 1995 to April 2002.

Presently, Dr. Deekshatulu is an ISRO Visiting Professor in the Dept. of Computer & Information Sciences, University of Hyderabad. Currently teaching and pursuing research in Image Processing.

Dr. M. Madhavi Latha graduated in B. Tech from NU in 1986, Post Graduation in M.Tech from JNTU in 1993 and Ph. D from JNTU in 2002. She has been actively involved in research and guiding students in the area of Signal & Image Processing, VLSI (Mixed Signal design) and hardware implementation of Speech CODECs. She has published more than 25 papers in National/ International Conferences and 3 papers in Journals. Currently, she has been working as Professor in ECE, JNTU College of Engineering, Hyderabad, Andhra Pradesh.