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SEARCHING QUERY BY COLOR CONTENT OF AN IMAGE USING INDEPENDENT COMPONENT ANALYSIS

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Abstract: Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision to the image retrieval problem, that is, the problem of searching for digital images in large databases. In CBIR each image which is stored in the database has its features extracted and compared to the features of the query image. The features that are to be used by the computer should correspond directly to routine notions of vision like color, texture, pattern and shape. In Content-based the search will analyze the actual contents of the image based on various parameters like color, shape, texture, or any other information which can be derived from the image itself. A major problem of feature-based characterizations of visual data is the high dimensionality of the feature spaces. The feature space becomes increasingly difficult to index efficiently with increased dimensionality. If the features are properly chosen, they may lend well to a natural hierarchy in indexing, or be constructed from a more advantageous space, which can be efficiently indexed.

Many indexing techniques are based on global features distribution such as Gabor Wavelets. [1]. In this paper we present an approach for global feature extraction using an 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:

ICA, Non Gaussianity, QBIC, YCbCr.

1. Introduction

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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.

One of the most important features which make possible the recognition of images by humans is color. Color is a property that depends on the reflection of light to the eye and the processing of that information in the brain. Color has been used everyday to tell the difference between objects, places, and the time of day. Usually colors are defined in three dimensional color spaces. These could either be RGB (Red, Green, and Blue), HSV (Hue, Saturation, and Value) or HSI (Hue, Saturation, and Brightness or intensity) or YCbCr (The luminosity, Chrominance of the blue primary, Chrominance of the red primary).

Retrieving images based on color similarity is achieved by computing a color histogram for each image that identifies the proportion of pixels within an image holding specific values (that humans express as colors). Examining images based on the colors they contain is one of the most widely used techniques because it does not depend on image size or orientation. Color searches will usually involve comparing color histograms, though this is not the only technique in practice.

In present work we dealt with all Color spaces : RGB,HIS,YCbCr etc. but in course of application it was found that YCbCr works well. YCbCr allows image compression techniques to take advantage that the eye is more discriminating of brightness levels than colour. Thus YCbCr tends to be particularly favoured for storing images, especially photograph images and video.

We have presented ICA of images as a computational technique for creating a new data dependent filter bank. The 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 approach is different from existing filtering methods in that it produces a data dependent filter bank.[3]

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 ICA. Section 3 describes ICA Algorithm where it is modified by taking PCA first (rather than whitening) so as to reduced the computational complexity by reducing the dimensions [1-2]. 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. Independent Component Analysis

Independent Component Analysis is a method for finding underlying factors or components from multivariate data. The approach that distinguishes ICA from other methods is that it looks for components that are both statistically independent and non-Gaussian.

In fact, in factor analysis it is often claimed that the factors are independent, but this is only partly true, because factor analysis assumes that the data has a Gaussian distribution. If the data is Gaussian, it is simple to find components that are independent, because for Gaussian data, uncorrelated components are always independent.

In reality, however, the data often does not follow a Gaussian distribution, and the situation is not as simple as those methods assume. For example, any real world data sets have super Gaussian distributions. This means that the random variables take relatively more often values that are very close to zero or very large. In other words, the probability density of the data is peaked at zero and has heavy tails (large values far from zero), when compared to a Gaussian density of the same variance. This is the starting point of ICA where statistically independent components are found, in general case where the data is non-Gaussian.

In the literature there are three different basic definition of ICA [3], here we are using the basic definition that, ICA of the random vector X consists of finding a linear transform

$$X = AS \quad (1)$$

So that the components 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. It may be surprising that the independent components can be estimated from linear mixtures with no more assumptions than their independence [1-6].

The principle used for determining the mixing matrix is independence. The components should be statistically independent which means that the value of any one of the components gives no information on the values of other components.

2.1 Gaussian Variables Are Forbidden

The phenomenon that the orthogonal mixing matrix cannot be estimated for Gaussian variables is related to the property that uncorrelated jointly distributed Gaussian variables are

necessarily independent. Thus the information on the independence of the components does not get us any further than whitening. Graphical distribution of orthogonal mixtures is same as distribution of ICs, as shown in Fig 1. It shows that the density is rotationally symmetric. Therefore it does not contain any information on the directions of the columns of the mixing matrix A . This is why A cannot be estimated.

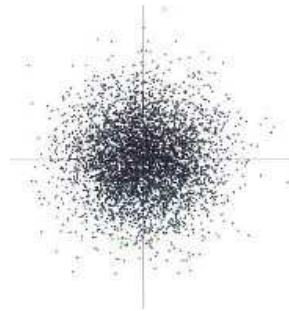


Fig 1. The multivariate distribution of two independent Gaussian Variables

Thus in the case of Gaussian independent components, we can only estimate the ICA model upto an orthogonal transformation. In other words, the matrix A is not identifiable for Gaussian independent components.

Thus if one try to estimate the ICA model, with some of the Gaussian and some non-Gaussian sources, then the non-gaussian components are estimated but the Gaussian components cannot be separated from each other. Actually in the case of just one Gaussian Component, the ICA model can be estimated, as the single Gaussian component does not have any other Gaussian Components that it could be mixed with.

3. ICA ALGORITHM

The properties of the ICA method depend on both of the objective function and the optimization algorithm. In particular the statistical properties depend on the choice of the objective function whereas the algorithm depends on the optimization function [3-6].

There are several different statistical criteria for estimation of the ICA model. Each of these criteria gives an objective function whose optimization enables ICA estimation. The present chapter deals with the different ICA algorithms, which depends on the following principles:

1. Maximization of Non Gaussianity
2. Maximum likelihood estimation

3. Minimization of mutual information
4. Tensorial Methods
5. Non Linear PCA

The detailed explanation for method 1 is given which is implemented for the present work with results in section 5.

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 $\mathbf{W}^T \mathbf{Z}$, where \mathbf{W} is the random matrix to be trained for finding ICA and \mathbf{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 \mathbf{Z} .
4. Choose the random mixing matrix \mathbf{W}
5. Orthogonalized the matrix \mathbf{W}
6. Let $\mathbf{W}_1 \leftarrow \mathbf{E} \{ \mathbf{Z} \mathbf{g}(\mathbf{W}^T \mathbf{Z}) \} - \mathbf{E} \{ \mathbf{g}'(\mathbf{W}^T \mathbf{Z}) \} \mathbf{W}$,
where \mathbf{g} is defined as
$$\mathbf{g}(y) = \tanh(y) \text{ or } \mathbf{g}(y) = y^3$$
- 7 Orthogonalized matrix \mathbf{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 $i = 1, 2, 3, \dots, m$

The filter bank consists of the ICA image basis \mathbf{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 [1]

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

$$E(m, n) = \sum_x \sum_y |F_{mn}(x, y)|, \quad (2)$$

$m=0, 1, \dots, M-1; n=0, 1, \dots, N-1$

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:

$$\mu_{mn} = \frac{E(m, n)}{P \times Q}$$
$$\sigma_{mn} = \sqrt{\frac{\sum_x \sum_y (|G_{mn}(x, y)| - \mu_{mn})^2}{P \times Q}} \quad (3)$$

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:

$$f = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \dots, \mu_{56}, \sigma_{56}). \quad (4)$$

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

$$D(Q, T) = \sum_m \sum_n d_{mn}(Q, T) \quad (5)$$

where

$$d_m = \sqrt{(\mu_m^Q - \mu_m^T)^2 + (\sigma_m^Q - \sigma_m^T)^2} \quad (6)$$

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

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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.

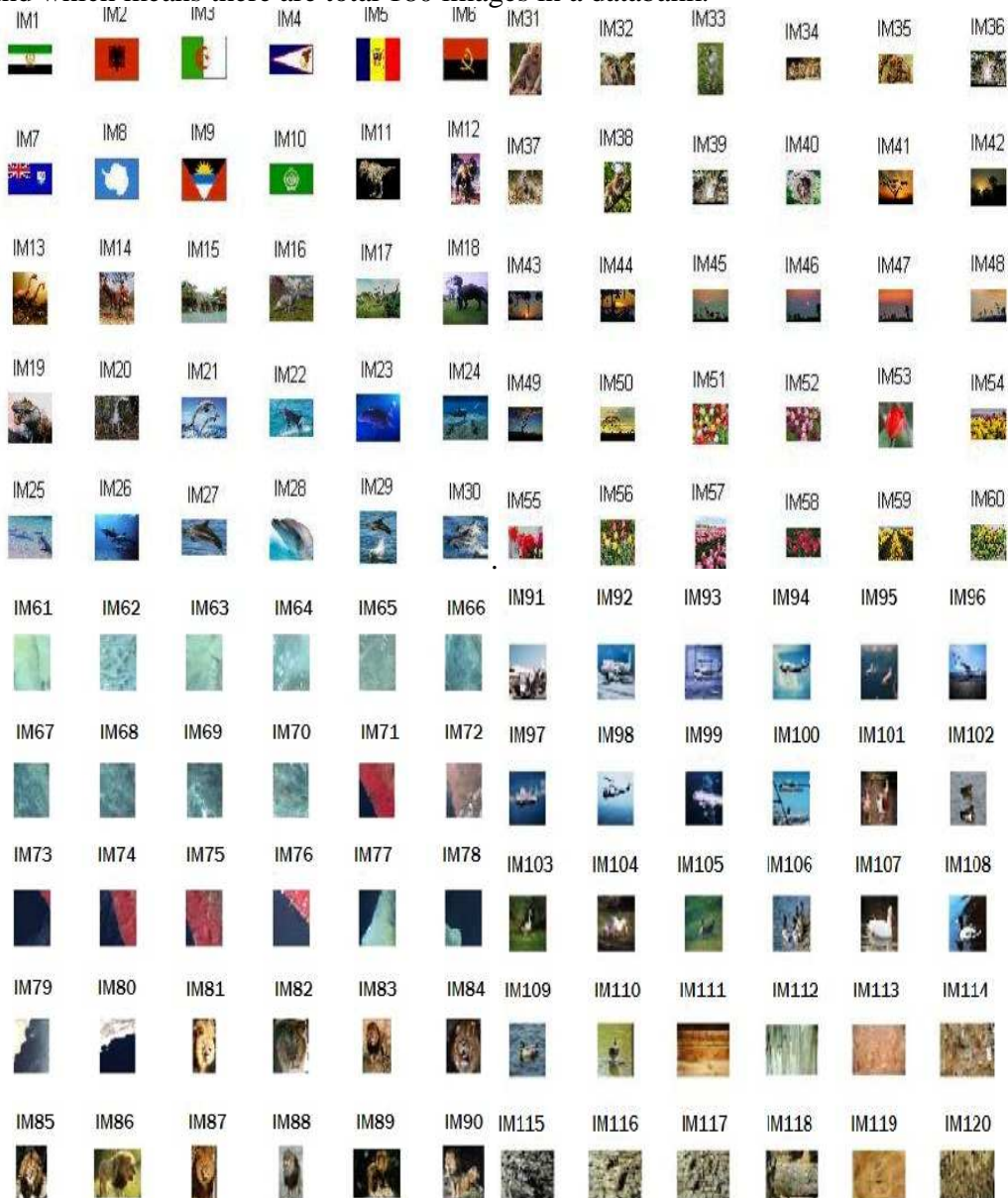




Fig 2. Databank used

Initially we use gray images as an input to ICA and Gabor algorithm. The first 32 retrieve images using ICA and Gabor are shown in Table 1 and Fig. 5. Table 1 gives the number of images retrieve out of 10 images in databank in first 32 retrieve images. For illustration we provide the results for flag and pebbles as query images where we found some interesting results with respect to their histogram. Fig. 3 and 4 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 or with nearly Gaussian distribution can be retrieve very efficiently by Gabor filters (Fig. 4), whereas the histogram which is having non Gaussian distribution can be retrieve very efficiently using ICA filters (Fig. 3). We found that these results are mostly true for other query images also.

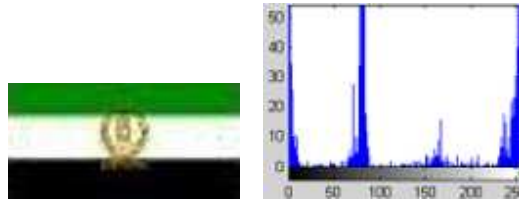


Fig 3. Flag as Query and its Histogram

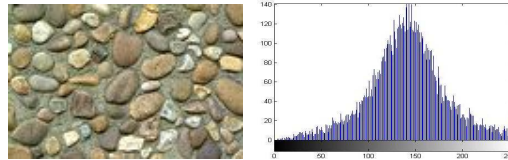


Fig 4. Pebbles as Query and its Histogram

Query	ICA	Gabor
Dinosaur	6	5
Dolphin	6	5
Flag	9	5
monkey	5	8
Nature	8	6
Tulip	6	7
Satellite 1	5	5
Satellite 2	4	7
Lion	6	7
Airplane	9	7
Duck	8	6
Wood	8	7
Tree	7	6
Clouds	9	7
Sand	6	7
Pebbles	4	10
Brick	6	4
Water	6	4

Table 1: Number of Retrieved query using ICA and Gabor

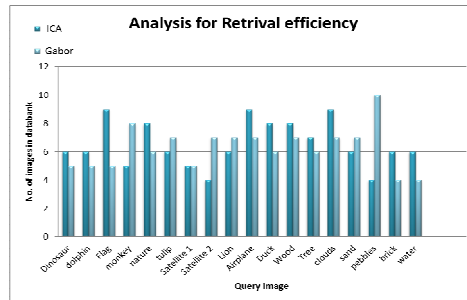


Fig 5. Comparative chart

From the above results where we got efficiency 60 % or less than 60% we tried to extend the algorithm for different color space like RGB, HIS and YCbCr. It was found that YCbCr works better as compared to other color spaces. The Table 2 and Fig 6 gives the analysis of retrieval with respect to these components. If we use color space YCbCr then the results are better than Gabor for nearly Gaussian distributed histogram also, but ICA fails for Gaussian distributed histogram as in the case of pebbles.

Query	ICA	Gabor	YCbCr
Lion	6	7	8
Satellite	5	5	9
Dolphin	6	5	7
Monkey	5	8	10
Pebbles	4	10	6

Table 2: Number of retrieved query using YCbCr model and ICA

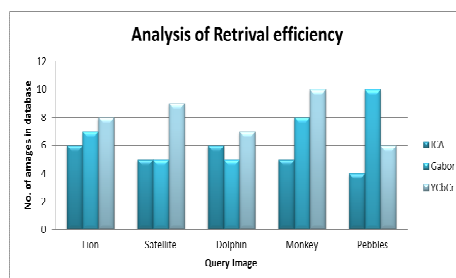


Fig 6. Comparative chart

6. Conclusion

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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.

Thus it can be seen that Gabor approach works well for Gaussian distributed data while ICA works well for non-Gaussian distributed data. The choice of applying Gabor or ICA for an image for feature extraction depends on the nature of the gray level distribution of the image data i.e. histogram. Thus the results agree with the basic assumption on ICA and Gabor, which is, Gabor is Gaussian modulated sinusoids whereas ICA is based on maximization of non-Gaussianity.

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