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Medical image retrieval using self-organising map on texture features

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Received 19 June 2018; accepted 24 October 2018
Available online 30 October 2018

Abstract

The process of capturing, transfer and sharing of information in the form of digital images have become easier due to the use of advanced technologies. Retrieval of desired images from these huge collections of image databases is one of the popular research areas and has its applications in various fields. An image set consists of images containing objects of different colours, shapes, orientations and sizes. The surface texture of the object in an image may also vary from another object in a different image. These factors make the process of image retrieval a difficult one. In this paper, Self-Organising Map is applied on local texture features for organising the brain magnetic resonance images according to their similarity. The correlation among the pixels is considered for the retrieval of most similar images to the input query image. The experimental results obtained prove the effectiveness of the proposed method for medical images.

Keywords: Self-organising map; Content-based image retrieval; Texture features; Text based retrieval; Spatial information; Classification

1. Introduction

The improvement in the technology used for capturing images and the development in the field of networking is the root cause of increase in the number of digital images. The process of searching and extracting the desired images from a large collection of image set is the aim of an image retrieval system. Retrieving the desired image from such a huge collection is one of the important research topic which has applicability in different areas like disease diagnosis, geographical information systems, engineering design, preventing crimes, digital libraries, military sector and many more. With the improvement in technology traditional methods of retrieval have been replaced by the computer-based methods, which reduces the time, money and labour required for manual searching [1].

The requirement of one user is different from another user. Also the type of information required is not uniform for all the users. So, different users may use different types of queries for retrieving their desired images from the image sets. Accordingly the queries can be textual queries, visual queries or attribute-based queries. Textual queries specify the image with the help of textual descriptions like title, keyword, descriptions of image etc., whereas visual queries use an image or visual characteristics like texture or colour as input. For extracting the desired image these inputs are compared with textual image descriptors and visual image descriptors in case of textual and visual queries respectively. Structural metadata and context values like image number, date are used in case of attribute-based queries for retrieving images. Basically image descriptors can be classified as metadata descriptors and visual descriptors. Text-based and attribute-based information come under metadata descriptors. Retrieval of an image is affected by the details and exactness of specifications provided in terms of queries and the capability of the system in understanding the query accurately and comparing these specifications with the image sets. To reduce the time of image retrieval metadata or image descriptors are used for comparison instead of matching every image stored [2].

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Peer review under responsibility of Faculty of Computers and Information Technology, Future University in Egypt.
Now-a-days content-based image retrieval has become one of the popular approach of image retrieval and is widely used in different areas. This paper contains a detailed analysis on the work done on this content-based image retrieval. The Content-based Image Retrieval (CBIR) which was introduced in the early 1980s is more popular as compared to the early approach of text-based retrieval. The CBIR technique was developed to overcome some of the important disadvantages of text-based retrieval namely, need of more human labour and time for annotation, inaccuracy in annotation etc. High-level features like keywords, descriptions in textual format are generally used as a similarity measure in text-based retrieval whereas low-level features like shape, texture, colour etc. are used in CBIR techniques [3].

According to Eakins [4] in CBIR there are three levels of queries level 1 is based on primitive features like texture, shape or colour, level 2 deals with derived features having some degree of logical inference. Level 3 retrieves with the help of abstract attributes containing the scenes and purpose of objects. Levels 2 and 3 are known as semantic image retrieval [3]. To manage the gap (semantic gap) between the low level features (level 1) and high level semantic concepts (level 2) relevance feedback techniques are used. In relevance feedback techniques the set of retrieved images are labelled as positive feedback (set of relevant images) and negative feedback (set of irrelevant images). The retrieval procedure is refined on the basis of this labelling. These processes are repeated again and again for getting better retrieval result. Two techniques of relevance feedback are query movement and biased subspace learning. A. Mohanan et al. performed a detailed analysis on relevance feedback techniques and their usefulness in image retrieval [5].

Section 2 describes the different types of image retrieval techniques and the types of primitive features used in content based image retrieval. The methodologies used by different researchers for image retrieval along with the use of self-organising map for different image processing and real world applications are given in section 3. Section 4 contains the proposed methodology followed by a description of self-organising map in section 5. Section 6 contains the experimental observations and discussions. Conclusion and future work is added in section 7.

2. Image retrieval techniques

Image retrieval techniques can be categorized as text based retrieval and content based retrieval techniques.

2.1. Text based retrieval

Text based retrieval retrieves images on the basis of text input. The text input which acts like a keyword, may be an image name, date, description of image etc. This approach has several disadvantages which may lead to an unsuccessful retrieval. Different persons may search for the same thing writing different types of queries. Search keyword may have some spelling mistakes. Sometimes the requirements cannot be expressed clearly or specified exactly. The extracted images may not be the exact match of the query image. To overcome these difficulties Content Based Image Retrieval (CBIR) techniques have been developed [6].

2.2. Content-based image retrieval

Opposite to the traditional concept-based approaches is the Content Based Image Retrieval (CBIR). CBIR is also popularly known as Content Based Visual Information Retrieval (CBVIR) or Query by Image Content (QBIC). This method of retrieval analyses the image contents like colour, texture, shape etc. for extracting images from large collection of databases. Traditional approaches are based on metadata search. Creating the metadata like tags, keywords, descriptions on the image is very time consuming, person dependent and may not be complete also [7].

CBIR was originated and named from an experiment for extracting images from a database considering the shape and colour features by T. Kato in 1992. First commercial application of CBIR was done by IBM named as QBIC (Query by Image Content). In CBIR approach the images can be extracted either by using different types of queries or comparing the image contents on the basis of some similarity measures. CBIR has a wide variety of application including crime investigation, military, medical diagnosis, face detection, remote sensing systems and many more [7].

2.2.1. Colour feature based retrieval

The main idea behind colour feature based retrieval is to construct a colour histogram of the image which shows the number of different colour pixels present in the image. The colour histogram of the query image is compared with the colour histograms of the images present in the database to retrieve the desired image. Besides colour histograms, Colour Coherent Vector (CCV), colour moments are also used for retrieval. In the retrieval process the colour descriptors which best represent similarity are extracted. In RGB colour model three primary colours Red, Green, Blue are present which are combined in appropriate proportion to generate any desired colour [8].

2.2.2. Shape feature based retrieval

Like colour shape is also one of the important characteristic which distinguish one object from another. A large number of research has already been done on this shape feature for retrieval [9]. Shape features must be invariant to rotation, scaling and translation for effective retrieval. Shape extraction techniques can consider factors like area, mass, solidity of the object etc. The edges and lines in the image are also extracted to determine the shape of the object [10].

2.2.3. Texture feature based retrieval

Image textures give information about the spatial arrangement of pixel gray levels which is very much essential for different image processing tasks like classification, segmentation and retrieval [11]. Colour features depend on the
intensities of the pixel and varies from pixel to pixel whereas texture features affect a region of the image. Texture of an image can be considered under different characteristics like contrast, direction, coarseness etc. Texture features represent the characteristics of image surface and also provides information about the shape, size, orientation, arrangement of objects present in the image. Texture features are used in texture segmentation, classification, synthesis etc. Segmentation partitions image surface into different parts based on the properties of texture features. In classification features are assigned with specific class labels depending on their similarity. As a result each class contains same type of features. Large textures are created from small ones using texture synthesis techniques which is used in texture mapping and also provides realistic views. Texture features are also used for reconstructing three dimensional surfaces [12].

Several methods are used for texture feature extraction like structural, statistical, model-based, transform information. Structural methods consider the spatial arrangement of image primitives. Though it gives a good representation of the image, it is not suitable for natural images due to the variation in macro-texture and micro-texture [12]. Statistical methods consider gray level information and tries to find out the relationship between the gray values. These techniques consider the spatial distribution of gray values and tries to find out a statistical relationship between these values. Depending on the number of pixels whose properties are considered statistical methods can be classified as first order, second order and higher order. First order statistics consider properties of a single pixel, second order statistics estimate relationship between pairs of pixels and higher order statistics analyses relationship between three or more pixels. Co-occurrence matrix is used to find second order statistical features which are popularly used for texture analysis. Intensity histogram of an image is first order statistical methods that finds four statistical intensity moments which is popularly used to calculate the intensity moment. For a 8-bit gray scale image I the maximum intensity value is $2^8 = 256$, that varies from 0 to 255 [12]. So the histogram of a 8-bit gray scale image contains 256 entries where each entry correspond to number of pixels having intensity value IV where $0 \leq IV \leq 255$. A lot of research work has been done for analysing different texture features like gray level co-occurrence matrix, Fourier spectrum, wavelet textures etc.

GLCM (Gray-Level Co-occurrence Matrix) is popularly used for extracting second order textual features and number of different gray levels in the image can be obtained from the number of rows and columns present in the image. Basically texture features are used to measure the intensity variations by computing the different gray level combinations present in the image. Two parameters relative distance and relative orientation are used for finding co-occurrence matrix. Relative distance depends on the number of pixels between two pixels and relative orientation is calculated considering different orientations. Out of fourteen GLCM features correlation, contrast, angular second moment, sum entropy, inverse difference moment are the most important features [12].

Another way of representing the texture information in a matrix format is with the help of Gray Level Run Length Matrix (GLRLM). Gray level run indicates those consecutive pixels which are having same gray levels. Run length is the number of pixels in a run. The number of runs having gray level i and length j is represented in the ith row and jth column of the GLRLM matrix. Features like Long Runs Emphasis (LRE), Short Runs Emphasis (SRE), Run Length Non-uniformity (RLNU), Gray Level Non-uniformity (GLNU), Run Percentage (RPERC) are obtained from GLRLM [12].

Local Binary Pattern (LBP) is one of the simplest and fastest approach of texture analysis that considers the neighbouring pixels for getting texture information. SIFT (Scale Invariant Feature Transform), Center-Symmetric LBP (CS-LBP), Volume-LBP, LPQ (Local Phase Quantization) are some of the similar features [12]. Auto correlation is one of the important parameter used to measure the coarseness of the surface which depends on the repetition of texture elements [12].

SGLD (Spatial Gray Level Dependency) matrix is another measure to evaluate the dependency and relationship between pixels in an image. A spatial relationship exists between two pixels which depends on the distance between the pixels and the angle. With this spatial relationship the SGLD matrix is constructed by calculating the joint probability of occurrence of gray levels of two pixels. A number of features can be extracted from SGLD matrix [12].

In this paper local gray level information is used to extract the texture information. Image is divided into small small regions and the gray level value of a pixel is calculated from its neighbourhood considering the pixels with highest gray level value and lowest gray level value. So, the value of a pixel is determined by the pixels in its neighbourhood and based on the idea of higher order statistics.

3. Related work

Different techniques are used for retrieval of images such as relevance feedback, wavelet transform, support vector machine, colour histogram, Gaussian mixture model etc. [13]. Some image retrieval approaches extract global texture and colour features and some take the help of local colour and texture features. For extracting local colour and texture features original image is divided into small blocks. These small regions act as the main building blocks for feature extraction and similarity comparison. So these systems are popularly known as RBIR (Region Based Image Retrieval) systems. For creating small blocks different segmentation techniques are used. Some of the RBIR systems use region-to-region similarity and some use image-to-image similarity. Different segmentation algorithms may segment the image in different ways and accordingly the segmented regions differ from each other in their contents and size. This problem can be solved by the image-to-image similarity which gives importance to a region depending on its size and a region may participate more than once in the matching process depending on its significance [14,15].
P. S. Hiremath et al. used texture, colour and shape information and considered original image and its complement for retrieving images. In their approach images are divided into non-overlapping regions. Texture and colour features are extracted from these regions at two separate resolutions in two grid structures. The colour and texture features obtained from conditional co-occurrence histograms along with shape features extracted using GVF (Gradient Vector Flow) help in finding the distance between images present in the database and the desired image. Canberra distance is used in their approach for finding similarity [14].

Applying the idea that the upper layer features in a Convolutional Neural Network (CNN) can act as good features A. Babenko et al. used upper layer features (referred as neural codes in their paper) of Convolutional Neural Network (CNN) for image retrieval [16].

M. Paulin et al. used the concept of representing an image in terms of patches for image retrieval. These patch based descriptors patch-CKN (Convolutional Kernel Networks) proved to be better and can be trained faster than SIFT (Scale Invariant Feature Transform) and other convolutional networks [17].

A. Gordo et al. developed a technique of image retrieval by creating a global representation of each image from the aggregation of several region descriptors. Their main contribution in deep architecture includes weight optimization and selection of regions for pooling [18].

Besides Convolutional neural network a lot of research has already been done to retrieve images using simple neural network techniques like Self-Organising Maps. The Self-Organising Maps along with a combination of techniques are used for retrieving colour as well as gray scale images.

J. Alnihoud used Self-Organising Map with fuzzy colour histogram and subtractive fuzzy clustering for content-based image retrieval. Self-organising Map is used for finding the best matching unit. The cluster in which query image lies is identified using fuzzy Colour histogram and subtractive fuzzy clustering techniques [19]. J. Laaksonen et al. applied a technique of image retrieval known as PicSOM based on the idea of neural network. The mapping from the image descriptor space to a two dimensional surface of nodes is performed using Self-Organising Map [20].

### Author(s) | Purpose | Technique used
---|---|---
A. Babenko et al. [16] | Image retrieval | Shape (GVF)
M. Paulin et al. [17] | Image retrieval | Neural Codes
A. Gordo et al. [18] | Image retrieval | Patch-CKN
J. Alnihoud [19] | Content-based image retrieval | SOM, Fuzzy Colour histogram, Subtractive fuzzy clustering
J. Laaksonen et al. [20] | Image retrieval | PicSOM
K. V. Laerhoven [21] | Classification of sensor data | SOM, K-means clustering
T. Li et al. [22] | Classification of costal water quality | SOM
D. K. Jain et al. [23] | Classification of hyperspectral images | SOM, SVM
A. K. Sahai et al. [24] | Improving forecast accuracy | SOM
Yen-Ping Tsai [25] | Relation between fish species and water quality | SOM
H. Mo et al. [26] | Segmentation of fabric prints | SOM

### 4. Proposed methodology

This paper suggests a method of retrieving medical images using self-organising map on texture features. Medical images lack colour information and normally gray in colour. So instead of considering the colour information, texture features are considered for image retrieval. For extracting texture features pixels in a $3 \times 3$ neighbourhood is considered and the value of any pixel is calculated as the difference between the maximum pixel value and minimum pixel value. So our approach uses a higher order statistical approach for extraction of local texture features. This technique is applied both on the query image and the images present in the image database. On these set of extracted features self-organising map algorithm is applied to group the images with similar features together and the weight matrix is updated accordingly. Using the weight matrix the correlation distance between the query image and other images are calculated. This helps in finding the correlation and dependency among each pixel in the image. The images are sorted according to the distance and finally the images are retrieved. The graphical representation of the proposed method is given in Fig. 1.
5. Self-organising map

Human brain receives information from various input sources like through ear in the form of audio, through eye in the form visual information. These information are processed in different regions of cerebral cortex in the brain. So, it gives rise to the need of a topological ordering of the information. The concept of self-organising maps developed from this topological ordering of information which is inspired neurobiologically. SOM is a widely used neural network models and uses the idea of unsupervised learning. So this technique can be applied when the class label information of the input is not known. The concept of SOM was given by Kohonen [27] and developed on the idea of competitive learning. Competitive learning is a category of unsupervised learning where the neurons in the output layer compete among themselves and the winning neuron can only be activated. This winning neuron decides the spatial location of topological neighbourhood of excited neurons, so that the neurons can cooperate with the neurons in its neighbourhood to create a map structure. In the synaptic adaptation stage the neurons adjust their weights. During the whole process the neurons organizes themselves to create a connected map structure, so this technique is known as self-organising map. This map preserves topology means that the nearby points in the input are also present closer to each other in the output. This can be achieved by maintaining the relative distance between the points. SOM maps a high dimensional continuous input space to a low dimensional discrete output space [28].

5.1. Competitive process

Suppose the number of inputs is $n$ then the input set $X$ to the network is $X_i$, where $i = 1, 2, \ldots, n$. If there are $m$ neurons in the computation layer, the neurons in the input layer and the computation layer are connected with weights $W_{ij}$, where $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$. The discriminant function can be defined as the Euclidean distance between the input layer and the neurons in the computation layer and can be represented as in equation (1):

$$d = \sum_{i=1}^{n} (X_i - W_{ij})^2$$

Neuron with lowest discriminant function is considered as the winning neuron in the competitive process.

5.2. Cooperative process

In a network the neurons present closer to each other interacts with each other and creates a neighbourhood depending on their spatial location. The topological neighbourhood function in SOM is maximum at the winning neuron and gradually decreases with increase in the distance from the winning neuron. This neighbourhood comprises of the winning neuron along with some excited neurons which cooperate with each other to create a map structure. Suppose $i$ is the winning neuron and $t_{ij}$ is the topological neighbourhood centered around the winning neuron surrounding the neuron $j$. A cooperation exists between neuron $i$ and $j$ and the topological neighbourhood is measured at point $j$. Let $d_{ij}$ is the lateral distance between winning neuron $i$ and excited neuron $j$. The extent to which the weights of excited neurons are adjusted depends on the topological neighbourhood. The neighbourhood function should be monotonically decreasing with distance $d_{ij}$ and symmetric about $d_{ij} = 0$. When $d_{ij} \to \infty$, it should decrease to zero. Gaussian function satisfies these two properties. Considering a Gaussian function topological neighbourhood can be defined as shown in equation (2):

$$d = \sum_{i=1}^{n} (X_i - W_{ij})^2$$

Neuron with lowest discriminant function is considered as the winning neuron in the competitive process.
where, $\sigma$ is the width of the Gaussian function and $i(X)$ indicates that it depends on the input vector $X$. The topological neighbourhood is translation invariant and does not depend on the position of the winning neuron.

Another property of SOM is that $\sigma$ is not constant with number of iterations. The value of $\sigma$ decreases with number of iterations, as a result neighbourhood shrinks with time. So $\sigma$ as a function of number of iterations can be represented as in equation (3)

$$\sigma(\text{noi}) = \sigma_0 \exp \left( -\frac{\text{noi}}{\tau} \right)$$

where, $\sigma_0$ is the initial value of $\sigma$, noi is the number of iterations which can have values $0, 1, 2, \ldots$ and $\tau$ is a time constant. So, neighbourhood function in equation (2) can be written as in equation (4).

$$h_{i(X),j}(\text{noi}) = \exp \left( -\frac{d_{ij}^2}{2\sigma^2(\text{noi})} \right)$$

A neuron may not always be the winner for all types of input patterns and different winning neurons may be there for different input patterns. As a result there must be some form of weight adjustment among the neurons. When the input patterns are very close to each other, the winners may be different but every neuron makes some weight adjustment. As a result the topology of the network is adjusted according to the input patterns. So the weight vectors attached with the output neurons are affected by the input patterns [28].

5.3. Adaptive process

In the synaptic weight adaptation process Hebbian learning is commonly employed for self organisation of neurons. The limitation of Hebbian learning is that, if the same pattern is given as input repeatedly then at some moment of time weights become saturated and cannot be increased further. To overcome this problem of saturation a forgetting term is used so that unlimited learning can be prevented in Hebbian approach. $f(Y_j)W_j$ is used as a forgetting term in Hebbian hypothesis, where $f$ is a positive scalar function and $Y_j$ is the output neuron $j$. Hebbian hypothesis with learning rate parameter $\eta$ is written as in equation (5)

$$\Delta W_j = \eta Y_j X$$

Using the forgetting term in Hebbian hypothesis, equation (5) becomes

$$\Delta W_j = \eta Y_j X - f(Y_j)W_j$$

Suppose $f$ is a linear function which can be defined as

$$f(Y_j) = \eta Y_j$$

Using equation (7) in equation (6), equation (8) can be derived.

Fig. 2. Original image.

\[ \Delta W_j = \eta Y_j X - \eta Y_j W_j \]  \hspace{1cm} (8)

Considering \( Y_j = h_{i(X),j} \) to include both winning and excited neurons in the topological neighbourhood, equation (8) can be rewritten as:

\[ \Delta W_j = \eta Y_j X - \eta h_{i(X),j} W_j = \eta h_{i(X),j} (X - W_j) \]  \hspace{1cm} (9)

So weights should be adjusted in such a way that it should move close to the input vector. Using discrete time formulation, equation (10) can be derived from equation (9)

\[ W_{j(noi + 1)} = W_{j(noi)} + \eta(noi)h_{i(X),j}(noi) (X - W_j) \]  \hspace{1cm} (10)

Initially learning rate \( \eta \) should be very high for quickly obtaining the topological ordering. When the topological
Fig. 6. Input weights for randomly selected 25 images.

Fig. 7. Initial weight matrix plot for randomly choosen 25 images.
Fig. 8. Result obtained after 500 iterations of Self-Organising Map.

Fig. 9. Result obtained after 1000 iterations of Self-Organising Map.
ordering is found and search for convergence starts. To decrease learning rate with time, equation (11) is used

\[ \eta(noi) = \eta_0 \exp \left( -\frac{\eta}{TC} \right) \]  

where, \( noi = 0, 1, 2, \ldots \) and \( TC \) is a time constant.

The adaptive process involves two phases, one is the ordering or self-organising phase and the other one is the convergence phase. The topology is arranged during the self-organising phase and the topology obtained is further fine-tuned during the convergence phase to reduce the error [28].

6. Experimental observations and discussions

For experimental verification of the proposed method, brain magnetic resonance images from TCIA collections are taken. TCIA is a large collection of cancer image archive. The images from CPTAC-GBM and CPTAC-CM Collections of TCIA are selected for analysis in this paper. The proposed method is implemented in MatLab R2015a with 4 GB RAM, 2.30 GHz speed Intel Core i5 processor. Fig. 2 shows the set of 25 brain MR images randomly chosen from the whole set of collected images. Local texture information is collected from these set of images considering the gray values in a \( 3 \times 3 \) neighbourhood. The gray value of a pixel is updated on the basis of the maximum and minimum pixel values in its neighbourhood. The extracted texture information is shown in Fig. 3.

Self-Organising Map technique is applied on these set of images (shown in Fig. 3) which contains the local texture information to give a better representation of the texture features. We have used \( 10 \times 10 \) nodes in the map for the implementation of the proposed technique. Fig. 4 shows the connections between the neighbours and Fig. 5 displays the weight distances between the neighbours in a self-organising map having 100 nodes. We have selected 25 images randomly for better visibility of the output. The weights associated with individual images are shown separately in Fig. 6. Fig. 7 gives a clear representation of the initial set of random weights associated with the selected 25 images. The weight matrix is updated during each iteration of the Self-Organising Map. The results obtained after 500 and 1000 iterations are given in Fig. 8 and Fig. 9 respectively. From these set of images it is clear that at each iteration the weight matrix is organized and improved. As a result gradual improvement in the arrangement of images according to their content similarity takes place. This can also be proved from Fig. 10, where the left side shows the initial set of weight vectors and right side shows the weight vectors after 1000 iterations. Comparing the left and right images of Fig. 10 one can say that the similar images are gradually grouped together with the increase in number of iterations.

The correlation between the values in the weight matrix is considered for retrieving the desired set of images form the image set containing brain magnetic resonance images. For

![Fig. 11. Query image.](https://digitalcommons.aaru.edu.jo/fcij/vol3/iss2/20)
better visibility nine retrieved images are shown in Fig. 12 for the query image given in Fig. 11.

From Fig. 12 it can be clearly observed that all the retrieved 9 images are similar to the query image. The experiment is repeated several times to calculate the accuracy of the proposed technique as given in Table 1. The accuracy of the proposed method can be obtained by finding the precision value. The precision is nothing but the ratio of number of relevant images retrieved and the total number of images retrieved.

\[
\text{Precision} = \frac{\text{Number of relevant images}}{\text{Total number of images retrieved}} \tag{12}
\]

When the same experiment is repeated several times it is found that, out of 9 either 8 or all the 9 retrieved images have similarity with the query image. As a result the accuracy varies between 88.88% and 100%. To obtain the accuracy of the proposed method the average accuracy is calculated which is found to be 93.33%.

7. Conclusion

This paper focuses on medical image retrieval using Self-Organising Map which is developed on the idea of neural network. For experimental verification magnetic resonance images of brain are considered and some images are chosen randomly for easy visualization of the obtained results. Medical images does not posses any colour, so for these types of images texture and shape features are considered for different image processing tasks. In this paper local texture information are extracted which is given as input to the Self-Organising Map algorithm. For retrieval of the images correlation between individual pixels are considered. Local and individual information of the pixels help in giving very good retrieval results which can be observed from the outputs obtained. Consideration of both spatial and high order statistical information also makes the method effective for image retrieval. This method can further be tested by applying it on colour images.

References


