A NOVEL FEATURE SELECTION MECHANISM FOR MEDICAL IMAGE RETRIEVAL SYSTEM

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ABSTRACT

Computer assistance has reached virtually in every domain with in the field of medical imaging. Dedicated Computer aided diagnosis (CAD) tools with proven clinical impact exist for narrow range of applications. Medical imaging modalities such as X-Rays, CT, MRI, CT-PET, and PET provide visual information for accurate diagnosis and indexed medical treatment. Now a days Medical databases are used automatically to classify the visual features for retrieving image which provides a Indexed reference for easy therapy. Medical image retrieval provides an archive for identifying the similar features with the given query image. In this work it is proposed to implement a novel feature selection mechanism using discrete sine transform. This classification results use support vector machine (SVM) which classifies kernel function, Regression values, Synaptic weights, Activation functions using multilayer perceptron neural network. The results obtained are performed with noise and blur to obtain noise free image which is further computed with statistical values and histogram processing to determine the accuracy of similar feature extracted.

KEYWORDS: *Support Vector machine (SVM), Multilayer Perceptron Neural Network, Statistical Values*

I. INTRODUCTION

In the clinical practice of reading and interpreting medical images, clinicians (i.e., radiologists) often refer to and compare the similar cases with verified diagnostic results in their decision making of detecting and diagnosing suspicious diseases. However, searching for and identifying the similar reference cases (or images) from the large and diverse clinical databases is a quite difficult task. The advance in digital technologies for computing, networking, and database storage has enabled the automated searching for clinically relevant and visually similar medical examinations (cases) to the queried case from the large image databases.

There are two types of general approaches in medical image retrieval namely, the text (or semantic) based image retrieval (TBIR) and the content-based image retrieval (CBIR). Features from query image are extracted by the same indexing mechanism. Then these query image features are matched with feature database using a similarity metric and, finally, similar images are retrieved. A majority of indexing techniques are based on pixel domain features such as color, texture and shape. Some frequency domain techniques include wavelet domain features, Gabor transform and Fourier domain features for feature extraction. Texture refers to the visual patterns that have properties of homogeneity not resulting from presence of only one color or intensity. It is an innate property of virtually all surfaces, including clouds, trees, bricks, hairs, fabric, etc. It contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment.

There are many pattern matching and machine learning tools and techniques for clustering and classification of linearly separable and non separable data. Support vector machine (SVM) is a relatively new classifier and it is based on strong foundations from the broad area of statistical learning theory.

Due to the huge growth of the World Wide Web, medical images are available in large numbers in online repositories, atlases, and other heath related resources. In such a web-based environment, medical images are generally stored and accessed in common formats such as JPEG (Joint Photographic Experts Group), GIF (Graphics Interchange Format), etc. These formats are used because they are easy to store and transmit compared to the large size of images in DICOM format, but also for anonymization purposes.

However, there is no header information attached to the images with these image formats other than DICOM format. In this case, the text-based approach is both expensive and ambiguous due to the fact that manually annotating these images is extremely time-consuming, highly subjective and requires domain-related knowledge. The content-based image retrieval (CBIR) systems overcome these limitations since they are capable of carrying out a search for images based on the modality, anatomic region and different acquisition views through automatically extracting visual information of the medical images. Currently, there exist some CBIR systems on medical image such as Med GIFT, COBRA and IRMA.

The CBIR extract the low level visual features such as color, texture, or spatial location automatically and the images are retrieved based on the low level visual features. Experiments demonstrate that the image retrieval performance can be enhanced when employing multiple features, since each feature extracted from images just characterizes certain aspect of image content and multiple features can provide an adequate description of image content. Further experiments also show that a special feature is not equally important for different image queries since a special feature has different importance in reflecting the content of different images.

II. BACKGROUND

The present work describes 2 types of existing methods for feature extraction. They are namely continuous wavelet transform and discrete wavelet transform

2.1. Discrete Wavelet Transform

The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The Wavelet Transform provides a time-frequency representation of the signal. It was developed to overcome the short coming of the Short Time Fourier Transform (STFT), which can also be used to analyze non-stationary signals. While STFT gives a constant resolution at all frequencies, the Wavelet Transform uses multi-resolution technique by which different frequencies are analyzed with different resolutions.

A wave is an oscillating function of time or space and is periodic. In contrast, wavelets are localized waves. They have their energy concentrated in time or space and are suited to analysis of transient signals. While Fourier Transform and STFT use waves to analyze signals, the Wavelet Transform uses wavelets of finite energy.

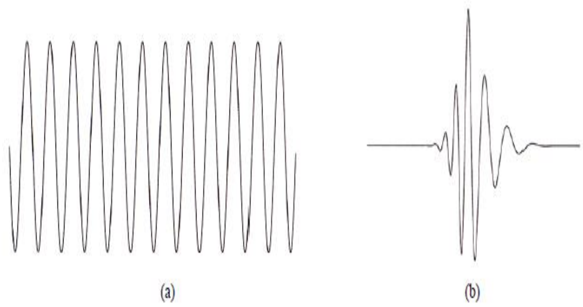

Figure1. Demonstrations of (a) a Wave and (b) a Wavelet.

The wavelet analysis is done similar to the STFT analysis. The signal to be analyzed is multiplied with a wavelet function just as it is multiplied with a window function in STFT, and then the transform is computed for each segment generated. However, unlike STFT, in Wavelet Transform, the width of the wavelet function changes with each spectral component. The Wavelet Transform, at high frequencies, gives good time resolution and poor frequency resolution, while at low frequencies, the Wavelet Transform gives good frequency resolution and poor time resolution.

The Wavelet Series is just a sampled version of CWT and its computation may consume significant amount of time and resources, depending on the resolution required. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required.

The foundations of DWT go back to 1976 when techniques to decompose discrete time signals were devised. Similar work was done in speech signal coding which was named as sub-band coding. In 1983, a technique similar to sub-band coding was developed which was named pyramidal coding. Later many improvements were made to these coding schemes which resulted in efficient multi-resolution analysis schemes.

In CWT, the signals are analyzed using a set of basic functions which relate to each other by simple scaling and translation. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cut off frequencies at different scales.

2.1.1. Dwt and Filter Banks

Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations, and the scale is determined by up sampling and down sampling (sub sampling) operation.

The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal as shown in figure 2.2. This is called the Mallet algorithm or Mallet-tree decomposition. Its significance is in the manner it connects the continuous time muter solution to discrete-time filters. In the figure, the signal is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by G0 while the high pass filter is denoted by H0. At each level, the high pass filter produces detail information, d[n], while the low pass filter associated with scaling function produces coarse approximations, a[n].

Highest frequency of ω, which requires a sampling frequency of 2ω radians, then it now, has a highest frequency of ω/2 radians. It can now be sampled at a frequency of ω radians thus discarding half the samples with no loss of information. This decimation by 2 halves the time resolution as the entire signal is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies and thus halves the resolution, the decimation by 2 doubles the scale. The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. The DWT of the original signal is then obtained by concatenating all the coefficients, a[n] and d[n], starting from the last level of decomposition. d1[n] .

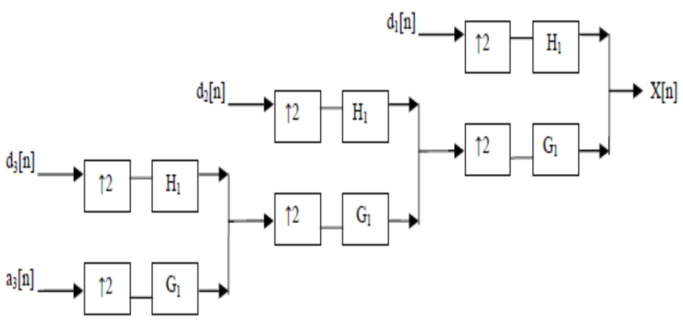

Figure 2. The reconstruction of the original signal from the wavelet coefficients. Basically, the reconstruction is the reverse process of decomposition. The approximation and detail coefficients at every level are up sampled by two, passed through the low pass and high pass synthesis filters and then added.

2.1.2. Classification of Wavelets

We can classify wavelets into two classes: (a) orthogonal and (b) biorthogonal. Based on the application, either of them can be used. Features of orthogonal wavelet filter banks. The coefficients of orthogonal filters are real numbers. The filters are of the same Length and are not symmetric.

The two filters are alternated flip of each other. The alternating flip automatically gives double-shift orthogonality between the low pass and high pass filters i.e., the scalar product of the filters, for a shift by two is zero. i.e., ∑G[k] H[k-2l] = 0, where k,lЄZ. Filters that satisfy equation 2.4 are known as Conjugate Mirror Filters (CMF). Perfect reconstruction is possible with alternating flip. Also, for perfect reconstruction, the synthesis filters are identical to the analysis filters except for a time reversal. Orthogonal filters offer a high number of vanishing moments. This property is useful in many signal and image processing applications. They have regular structure which leads to easy implementation and scalable architecture.

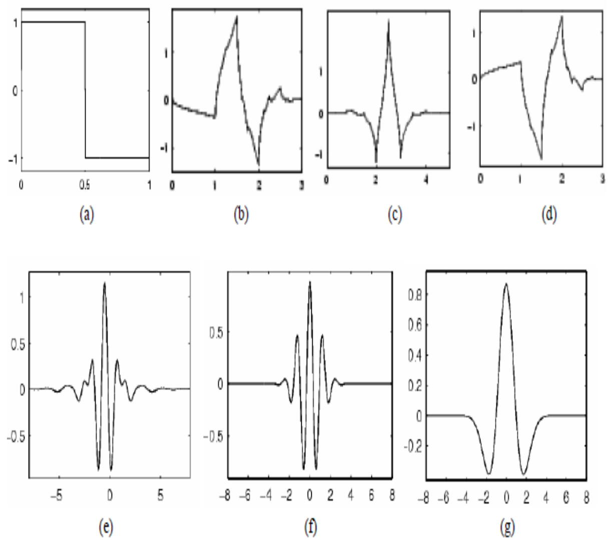

Figure3. Wavelet Families(a)Haar (b)Daubechies4 (c) Coiflet1 (d)Symlet2 (e)Meyer (f) Morlet (g) Mexigan Hat

In the case of the biorthogonal wavelet filters, the low pass and the high pass filters do not have the same length. The low pass filter is always symmetric, while the high pass filter could be either symmetric or anti-symmetric. The coefficients of the filters are either real numbers or integers. For perfect reconstruction, biorthogonal filter bank has all odd length or all even length filters. The two analysis filters can be symmetric with odd length or one symmetric and the other anti symmetric with even length. Also, the two sets of analysis and synthesis filters must be dual. The linear phase biorthogonal filters are the most popular filters for data compression applications.

2.2. The Continuous Wavelet Transform and the Wavelet Series

The Continuous Wavelet Transform (CWT) is provided by equation. Where x(t) is the signal to be analyzed. $\psi(t)$ is the mother wavelet or the basis function. All the wavelet functions used in the transformation are derived from the mother wavelet through translation (shifting) and scaling (dilation or compression).

The mother wavelet used to generate all the basic functions is designed based on some desired characteristics associated with that function. The translation parameter relates to the location of the wavelet function as it is shifted through the signal. Thus, it corresponds to the time information in the Wavelet Transform. The scale parameter s is defined as |1/frequency| and corresponds to frequency information.

Scaling either dilates (expands) or compresses a signal. Large scales (low frequencies) dilate the signal and provide detailed information hidden in the signal, while small scales (high frequencies) compress the signal and provide global information about the signal. Notice that the Wavelet transform merely performs the convolution operation of the signal and the basis function. The above analysis becomes very useful as in most practical applications, high frequencies (low scales) do not last for a long duration, but instead, appear as short bursts, while low frequencies (high scales) usually last for entire duration of the signal.

The Wavelet Series is obtained by discrediting CWT. This aids in computation of CWT using computers and is obtained by sampling the time-scale plane. The sampling rate can be changed accordingly with scale change without violating the Nyquistcriterion. Nyquistcriterion states that, the minimum sampling rate that allows reconstruction of the original signal is 2ω radians, where ω is the highest frequency in the signal. Therefore, as the scale goes higher (lower frequencies), the sampling rate can be decreased thus reducing the number of computations.

2.2.1. Pyramidal Structure Wavelet Transform

Efficient texture representation is important in rotation invariant texture image retrieval. It is obvious that texture features which can efficiently define directional and spatial/frequency characteristics of the patterns, will always lead to good texture analysis and retrieval result. This is possible with Gabor wavelet and steerable pyramid by considering more number of orientations, but that increases the redundancy heavily because of non orthogonality property and makes it unsuitable for online application. On the other hand to avoid computational complexity previous attempts have been made to obtain rotation invariant texture features using real discrete wavelet transform (DWT). But texture representation with the real DWT has two main disadvantages of shift sensitivity and poor directionality (only three directions information) .Texture feature extraction with DWT gives the edge information in the horizontal, vertical and diagonal direction.

Another technique has been examined called the pyramid-structured wavelet transform for texture classification. Its name comes from the fact that it recursively decomposes sub signals in the low frequency channels. It is mostly significant for textures with dominant frequency channels. For this reason, it is mostly suitable for signals consisting of components with information concentrated in lower frequency channels.

Due to the innate image properties that allows for most information to exist in lower sub-bands, the pyramid-structured wavelet transform is highly sufficient. Using the pyramid-structured wavelet transform, the texture image is decomposed into four sub images, in low- low, low-high, high-low and high-high sub-bands. At this point, the energy level of each sub-band is calculated. This is first level decomposition. Using the low-low sub-band for further decomposition, this paper is reached third level decomposition. The reason for this is the basic assumption that the energy of an image is concentrated in the low-low band.

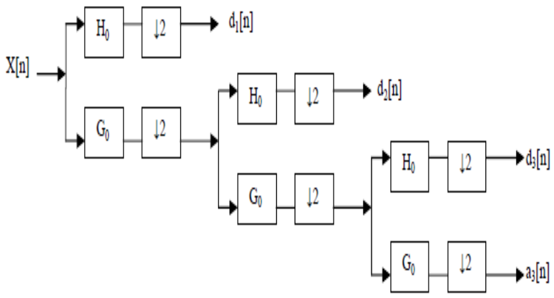

Figure4. Three level decomposition technique

2.3. Proposed Method:

Digital medical images take up most of the storage space in the medical database. Digital images are in the form of X-Rays, MRI, CT. These medical images are extensively used in diagnosis and planning treatment schedule. Retrieving required medical images from the database in an efficient manner for diagnosis, research and educational purposes is essential. Image retrieval systems are used to retrieve similar images from database by inputting a query image. Image retrieval systems extract features in the image to a feature vector and use similarity measures for retrieval of images from the database. So the efficiency of the image retrieval system depends upon the feature selection and its classification. In this paper, it is proposed to implement a novel feature selection mechanism using Discrete Sine Transforms (DST) with Information Gain for feature reduction. Classification results obtained from existing Support Vector Machine (SVM) is compared with the proposed Support Vector Machine model. Results obtained show that the proposed SVM classifier outperforms conventional SVM classifier and multi layer perceptron neural network.

III. IMPLEMENTATION & OPTIMIZATION

The block diagram of an image retrieval system Image retrieval plays a fundamental role in handling large amount of visual information in medical applications.

3.1. System Design

Query image:

Query image is the image which is selected from database to compare the database images.

***Input images*:**

Digital medical images take up most of the storage space in the medical database. Digital images are in the form of X-Rays, MRI, CT. These medical images are extensively used in diagnosis and planning treatment schedule. Retrieving required medical images from the database in an efficient manner for diagnosis, research and educational purposes is essential Retrieving required medical images from the database in an efficient manner for diagnosis, research and educational purposes is essential. Image retrieval systems are used to retrieve similar images from database by inputting a query image.

3.2. Image database

Database mainly used to store the images but here we didn't any data base. In images MATLAB we maintain a folder to store the images. By using model function call the images from folder for the processing of comparison. A CT scan shows detailed images of any part of the body, including the bones, muscles, fat, and organs. Spatial and contrast resolution are dependent on the energy of the x-ray source, slice thickness, field of view, and scanning matrix. High resolution CT provides excellent delineation of osseous structures.

In this system six different categories of CT scan images used for retrieval, 20 images in each category so total 120 images store in database from that one image of each group shown in figure . This data collect from Nobel hospital, Pune and some of the images available at internet. Each image has different size but we can convert in fixed size form by using Matlab command resize that is 256 X 256 size.

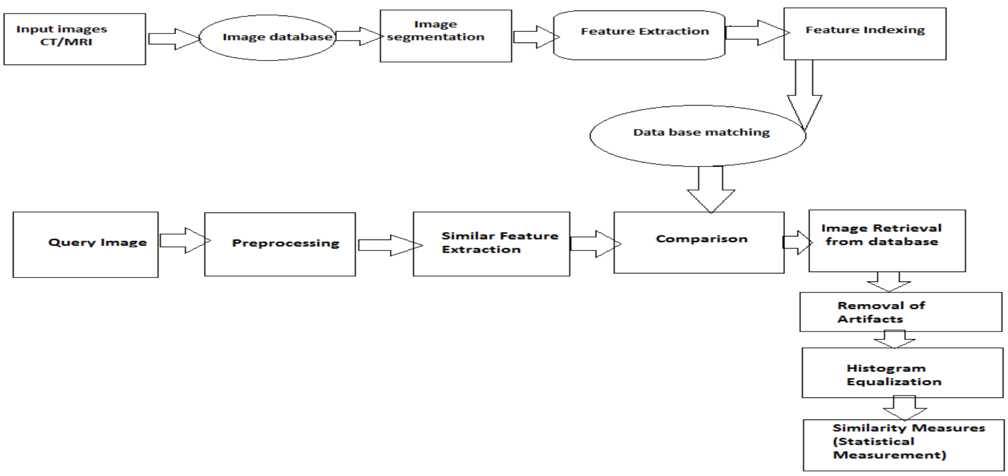

Figure5. Block Diagram for image retrieval

Figure6. Database Images

The feature vectors of the image constitute a feature dataset stored in the database. In online image retrieval, the user can submit a query example to the retrieval system in search of desired images. The

system represents this example with a feature vector. The distances (i.e., similarities) between the feature vectors of the query example and those of the media in the feature dataset are then computed and ranked.
Retrieval is conducted by applying an indexing scheme to provide an efficient way of searching the image database. Finally, the system ranks the search results and then returns the results that are most similar to the query examples. If the user is not satisfied with the search results, the user can provide relevance feedback to the retrieval system, which contains a mechanism to learn the user's information needs. The following sections will clearly introduce each component in the system.

Image segmentation:

Segmentation partitions an input image into its constituent parts or objects. The output of segmentation stage is raw pixel data constituting either the boundary of a region or all points in the region itself.

3.3. Feature extraction

Representation of images needs to consider which features are most useful for representing the contents of images and which approaches can effectively code the attributes of the images. Feature extraction of the image in the database is typically conducted off-line so computation complexity is not a significant issue. This section will introduce two features — texture and color — which are used most often to extract the features of an image.
A feature is a characteristic that can capture a certain visual property of an image either globally for the whole image, or locally for objects or regions. Content based image retrieval, a sub domain of computer vision, is a system in which a computer analysis an image to extract visual features. These features are known as low level features. Some key issues related to FBIR systems are the following, first how the extracted features can present image contents. Second, how to determine the similarity between images based on their extracted features. One technique for these issues is using vector model. This model represents an image as a vector of features and the difference between two images is measured via the distance between their feature vectors.
Feature extraction module extract and save image features to the feature database automatically. Texture is one of the most important features for FBIR. Texture refers to the visual patterns that have properties of homogeneity not resulting from presence of only one color or intensity. Texture features are extracted from co-occurrence matrices and wavelet transforms coefficients.
This paper has shown how one can use new transform is complex wavelet transform (DST) to enhance the image retrieval process. They have shown that we can achieve almost the same precision for color image retrieval as well. These properties of CWT have motivated us to use it as feature extraction for our proposed system.

3.4. *Feature indexing*

Retrieval of an image is usually based not only on the value of certain features, but also on the location of a feature vector in the multi-dimensional space.

The R-tree, which is a tree-like data structure, is mainly used for indexing multi-dimensional data. Each node of an R-tree has a variable number of entries. Each entry within a non-leaf node can have two pieces of data. The goal of the R-tree is to organize the spatial data in such a way that a search will visit as few spatial objects as possible.

3.5. Database comparison

Selection of similarity metrics has a direct impact on the performance of feature-based image retrieval. The kind of feature vectors selected determines the kind of measurement that will be used to compare their similarity (Smolders, Warring, Santana, Gupta, & Jain, 2000). If the features extracted from the images are presented as multi-dimensional points, the distances between corresponding multi-dimensional points can be calculated.
Support Vector Machines (SVM's) are a relatively new learning method used for binary classification. The basic idea is to find a hyper plane which separates the d-dimensional data perfectly into its two classes. However, since example data is often not linearly separable, SVM's introduce the notion of a \kernel induced feature space" which casts the data into a higher dimensional space where the data is

separable. Typically, casting into such a space would cause problems computationally, and with obverting.
The key insight used in SVM's is that the higher-dimensional space doesn't need to be dealt with directly (as it turns out, only the formula for the dot-product in that space is needed), which eliminates the above concerns. Furthermore, the VC-dimension (a measure of a system's likelihood to perform well on unseen data) of SVM's can be explicitly calculated, unlike other learning methods like neural networks, for which there is no measure. Overall, SVM's are intuitive, theoretically well- founded, and have shown to be practically successful. SVM's have also been extended to solve regression tasks (where the system is trained to output a numerical value, rather than \yes/no" classification).
There are many pattern matching and machine learning tools and techniques for clustering and classification of linearly separable and non separable data. Support vector machine (SVM) is a relatively new classifier and it is based on strong foundations from the broad area of statistical learning theory . It is being used in many application areas such as character recognition, image classification, bioinformatics, face detection, financial time series prediction etc.

3.6. Relevance Feedback

Relevance feedback was originally developed for improving the effectiveness of information retrieval systems. The main idea of relevance feedback is for the retrieval system to understand the user's information needs. For a given query, the retrieval system returns initial results based on pre-defined similarity metrics. Then, the user is required to identify the positive examples by labelling those that are relevant to the query. The system subsequently analyzes the
User's feedback using a learning algorithm and returns refined results.
A typical relevance feedback mechanism contains a learning component and a Dispensing component. The learning component uses the feedback data to estimate the target of the user. The approach taken to learn feedback data is key to the relevance feedback mechanism.
Removal of artifacts: If the has been blurred or noise is added to that image that blurriness can be removed by using different types of reconstruction filters. They are

1. Mean filters
2. Order static filters
3. Adaptive filters

Histogram equalization:

The histogram equalization method is quite useful but it is not suitable for image enhancement applications because the capabilities of this method are limited to the generation of only one result that is an approximation to a uniform histogram. It is often desirable to specify interactively particular histograms capable of highlighting certain gray level range in an image.

Statistical measurements:

Statistical analysis is going to be performed on an image by calculating some parameters such as: Standard deviation, Peak signal to noise ratio, Mean square error, Entropy

IV. METHODS

4.1. Discrete sine transform

DCTs and DSTs are members of the class of sinusoidal unitary transforms .A sinusoidal unitary transform is an invertible linear transform whose kernel describes a set of complete, orthogonal discrete cosine and/or sine basis functions. The well-known Karhunen–Loève transform (KLT) generalized discrete Fourier transform generalized discrete Hartley transform or equivalently generalized discrete W transform, and various types of the DCT and DST are members of this class of unitary transforms.
The set of DCTs and DSTs introduced by Jain is not complete. The complete set of DCTs and DSTs, so-called discrete trigonometric transforms, has been described by Wang and Hunt. The family of discrete trigonometric transforms consists of 8 versions of DCT and corresponding 8 versions of DST.

Each transform is identified as even or odd type. All present digital signal and image processing applications (mainly transform coding and digital filtering of signals) involve only even types of the DCT and DST.

A discrete cosine transform (DCT) expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering, from lossy compression of audio (e.g. MP3) and images (e.g. JPEG) (where small high-frequency components can be discarded), to spectral methods for the numerical solution of partial differential equations.

The use of cosine rather than sine functions is critical in these applications: for compression, it turns out that cosine functions are much more efficient (as described below, fewer functions are needed to approximate a typical signal), whereas for differential equations the cosines express a particular choice of boundary conditions.

In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the Fourier transform of a real and even function is real and even), where in some variants the input and/or output data are shifted by half a sample.

The feature vector from each image was extracted using the discrete sine transform. Pixels which are one length away from each other are selected. The algorithm pseudo is given below:

1. Compute Image size MxN
2. For each alternate value 'I' in array M and array size less than M or M+1
3. For each alternate value 'j' in array N and array size less than N or N+1
4. Compute DST(array[xi, yj])
5. Store computed value in one dimensional array
6. Repeat from step 1 till all images are computed

The discrete sine transform (DST) is similar to the discrete Fourier transform (DFT) but with the difference of using only the real numbers. The discrete sine transform is represented by(1)

$$S_k = p_K \sum_{n=0}^{N-1} x_n \sin \frac{\pi (n+\frac{1}{2})(k+1)}{N} \quad k = 0,1,2,.........,N-1$$

$$p_k = \sqrt{\frac{2-\delta_{k,0}}{N}} \qquad ....(1)$$

The remarkable fact is that, unlike common situations, the eigenvectors of a MA(1) process are universal as they are given by the orthonormal basis used in the Discrete Sine Transform (DST). Moreover the Eigen values of the DST components are ordered, separated and all non degenerate. Given that the Karhunen-Loève expansion represents the optimal solution to a linear filtering problem, this nonparametric property can be very useful for real-time analysis of high frequency return data as it provides an universal basis to optimally decorrelate the price signal.

Another way to construct a simple volatility estimator from the DST decomposition is to evaluate _2 M for different values of M and then perform a simple linear regression on the equation (1). Then the intercept is an unbiased (not only asymptotically but also infinite sample) estimator of the instantaneous volatility. We call this measure Fitted DST estimator. This approach would be particularly useful when the number of observations is not very high and thus sufficiently large values of M are not attainable.

Discrete sine transform is preferred over Fast Fourier transform due to its simplicity and the reduced time to compute the medical image coefficients.

Information Gain

Information gain selects the feature vectors which are essential for the classification process. On the computed coefficient from DST, the information gain can be computed based on the class attribute. The information gain that has to be computed for an attribute *X* whose class attribute *Y* is given by the conditional entropy of *Y* given *X, H (Y|X)* is given by (3)

I(Y; X) =H(Y)-H(Y/X)

The conditional entropy of *Y* given *X* is

$$H(Y/X) = - \square P(X=x1)\ H(Y|X=x1) \qquad .... (2)$$

4.2. Support Vector Machine

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SVM offers many advantages over other classification methods such as neural networks. Support vector machines have many advantages in comparison with other classifiers. There are computationally very efficient as compared with other classifiers, especially neural networks.

• They work well, even with high dimensional data. And with less number of training data.

• They attempt to minimize test error rather than training error.

• They are very robust against noisy data.

• The curse of dimensionality and over fitting problems does not occur during classification.

Fundamentally, SVM is a binary classifier, but can be extended for multi-class problems as well. The task of binary classification can be represented as having, (Xi, Yi) pairs of data. Where Xi∃ Xp, a p dimensional input space and Yi∃ [−1, 1] for both the output classes. SVM finds the linear classification function $g(x)$ = W.X+b, which corresponds to a separating hyper plane W. X+b = 0, where wand *b* are slope and intersection.

Different options exist to extend SVM for multi class cases; these include one against all, one against one and all at once. Figure 3.1 shows how one against all SVM can be used for grouping of different classes inside an image database. Each support vector machine separates one class of images from the rest of the database.

Support vector machine (SVM) is a linear machine which constructs a hyper plane as a decision surface. It is based on the method of structural risk minimization; the error rate is bound by the sum of the training-error rate and a term that depends on the Vapnik-Chervonenkis (VC) dimensions. The SVM provides good generalization performance on pattern classification. The principle of SVM algorithm is based on the inner-product kernel between a “support vector” xi and the vector x drawn from the input vector.

In this paper it is proposed to modify the existing poly kernel of Support Vector Machine (SVM). The proposed Gaussian poly kernel of SVM, GPK-SVM is derived as follows. The function $K(x, y)$ is a kernel function if it satisfies.

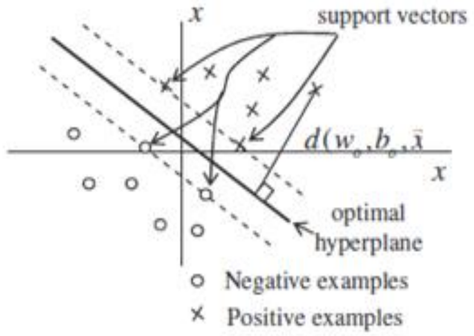

Figure7. one against all classification showing three support vector machines.

Machine Learning is considered as a subfield of Artificial Intelligence and it is concerned with the development of techniques and methods which enable the computer to learn. In simple terms development of algorithms which enable the machine to learn and perform tasks and activities. Machine learning overlaps with statistics in many ways. Over the period of time many techniques and methodologies were developed for machine learning tasks.

Support Vector machines can be defined as systems which use hypothesis space of a linear functions in a high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory. Support vector machine was initially popular with the NIPS community and now is an active part of the machine learning research around the world.

SVM becomes famous when, using pixel maps as input; it gives accuracy comparable to sophisticated neural networks with elaborated features in a handwriting recognition task. It is also being used for many applications, such as hand writing analysis, face analysis and so forth, especially for pattern classification and regression based applications.

The foundations of Support Vector Machines (SVM) have been developed by Vapnik and gained popularity due to many promising features such as better empirical performance. The formulation uses the Structural Risk Minimization (SRM) principle, which has been shown to be superior, to traditional Empirical Risk Minimization (ERM) principle, used by conventional neural networks.

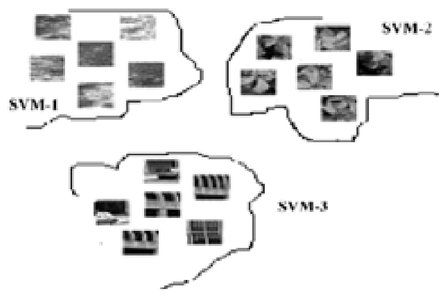

Figure8. Linear separable

SRM minimizes an upper bound on the expected risk, where as ERM minimizes the error on the training data. It is this difference which equips SVM with a greater ability to generalize, which is the goal in statistical learning. SVMs were developed to solve the classification problem, but recently they have been extended to solve regression problems.

Support Vector Machines (SVM) is an approximate implementation of the structural risk minimization (SRM) principle. It creates a classifier with minimized Vapnik- Chervonenkis (VC) dimension. SVM minimizes an upper bound on the generalization error rate. The SVM can provide a good generalization performance on pattern classification problems without incorporating problem domain knowledge. Consider the problem of separating the set of training vectors belonging to two classes:

A linear separable example in 2D is illustrated in figure4.2 An optimal hyper plane is constructed for separating the data in the high-dimensional feature space. This hyper plane is optimal in the sense of being a maximal margin classifier with respect to the training data.
The distance indicates how much an example belonging toone class is different from the other one. These motivate us to use SVM for automatically generating preference weights for relevant images. Intuitively, the farther the positive examples from the hype plane, the more distinguishable they are from the negative examples.
Thus, when we decide their preference weights, they should be assigned with larger weights. Currently, we simply set the relation between the preference weights and the distance as a linear relation in the numerical calculation. It can be easily extended to nonlinear relation. During the iterative query procedure, the positive and negative examples selected in the history are collected for learning at each query time.
Support Vector Machines (SVM) is a powerful, state-of-the-art algorithm with strong theoretical foundations based on the Vapnik-Chervonenkis theory. SVM has strong regularization properties. Regularization refers to the generalization of the model to new data.

4.2.1 Advantages of SVM

SVM models have similar functional form to neural networks and radial basis functions, both popular data mining techniques. However, neither of these algorithms has the well-founded theoretical approach to regularization that forms the basis of SVM. The quality of generalization and ease of training of SVM is far beyond the capacities of these more traditional methods.SVM can model complex, real-world problems such as text and image classification, hand-writing recognition, and bioinformatics and bio-sequence analysis. SVM performs well on data sets that have many attributes, even if there are very few cases on which to train the model. There is no upper limit on the number of attributes; the only constraints are those imposed by hardware. Traditional neural nets do not perform well under these circumstances
SVM classification is based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships. SVM finds the vectors ("support vectors") that define the separators giving the widest separation of classes.

V. EXECUTION RESULTS

A novel feature based image retrieval system results are shown below:

5.1 GUI format

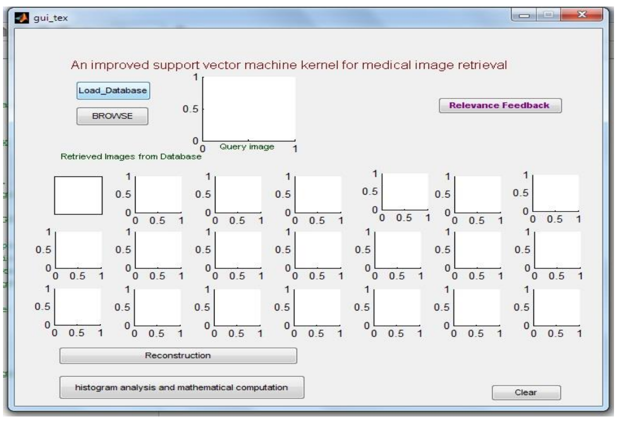

Figure9. GUI model for image retrieval

The above figure shows the GUI model for image retrieval system. It consist mainly five push buttons. They are namely

1. Load data base
2. Browse
3. Relevance feed back
4. Removal of artefacts

5. Histogram analysis mathematical computations

Load database

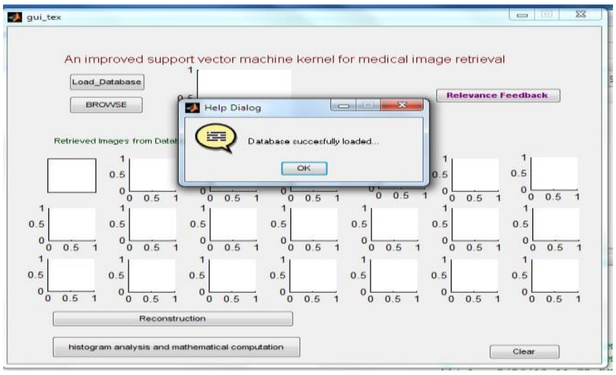

Figure10. After loading database, pop-up window is appeared

The above figure comes into display after loading the database. A help dialog window displays on the display screen. If the database is loaded, then it displays as Database successfully loaded.

Browse

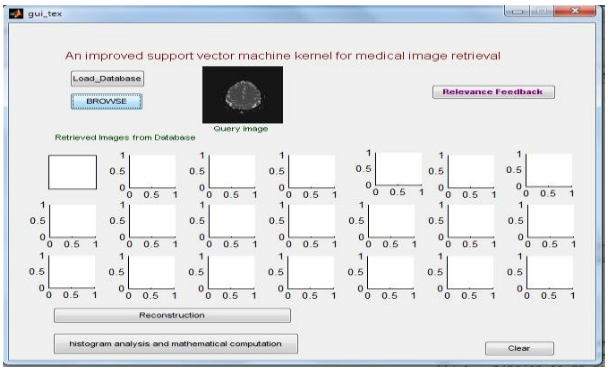

Figure11. Inserting query image

After loading the database data successfully. Then the matlab prrogram is ready for taking the query images for the part of executing the program. After pushing it, the query image load in the axis.

Relevance feed back

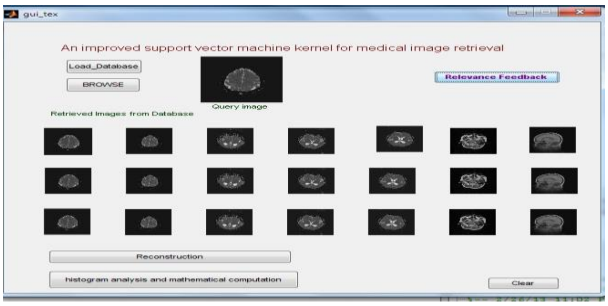

Figure12. Relevance call back image

Then we are looking for the related images are present in the database or else it doesn't contain any related images. For these we will push the relevance feedback push button. If displays the related images which are present in the database.

5.2 Removal of artifacts

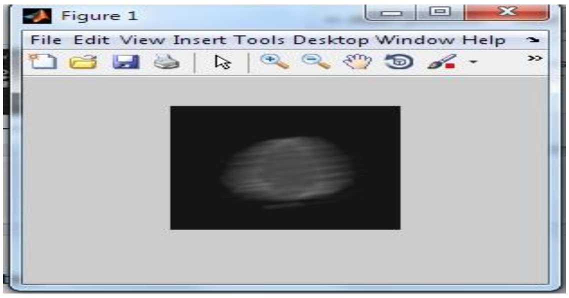

Figure13. Blur and noise containing query image

This is the original blur and noise image that are taken for removal of artifacts.

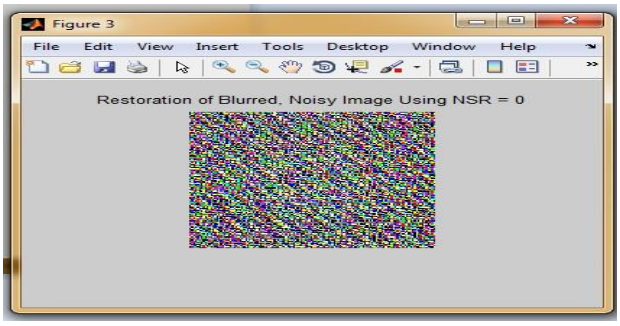

Figure14. Restoration of Blurred, Noisy Image Using NSR=0

Figure15. Removal of blur and noise in the image

The above figure shows that the added pepper noise for removal of blur and noise which are present in the image. The original blur and noise image and restoration of blurred image sum up and cancelled the noise and blurriness present in the image. Later it extract the extracted image without any blur and noise.

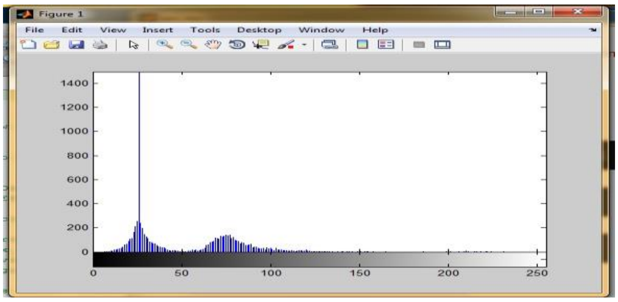

Figure16. Histogram for the query image

The figure explains the histogram equalization. It shows the intensity levels of the image pixels with respect to time axis.

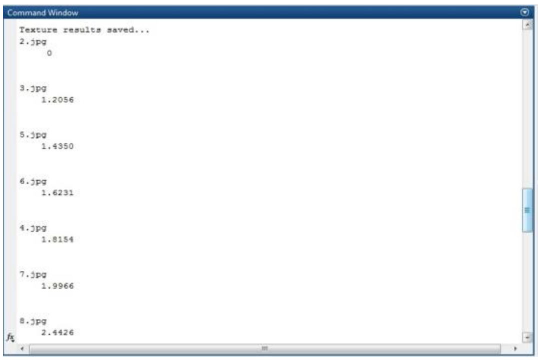

Figure17. Command having relevance feedback values

The above values are mean and standard deviation Based on the query image used in the program code the relevance feedback values on comparison.

VI. CONCLUSIONS

In this paper it was proposed to extract features using Discrete Sine Transform (DST) and select the top 50 attributes based on class attribute using information gain. The extracted features were trained and classified with SVM using poly kernel. A novel SVM was proposed and the classification accuracy of the proposed method improves by a factor of 5.18.The reduced features in the proposed method, decreases the overall processing time for a given query input image.

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