IMAGE RETRIEVAL SYSTEM BY USING CWT AND SUPPORT VECTOR MACHINES

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Abstract

This paper presents an image retrieval system based on dual tree complex wavelet transform (CWT) and support vector machines (SVM). There are two attributes of image retrieval system. First, images that a user needs through query image are similar to a group of images with the same conception. Second, there exists non-linear relationship between feature vectors of different images. Standard DWT (Discrete Wavelet Transform), being non-redundant, is a very powerful tool for many non-stationary Signal Processing applications, but it suffers from three major limitations; 1) shift sensitivity, 2) poor directionality, and 3) absence of phase information. To reduce these limitations, Complex Wavelet Transform (CWT). The initial motivation behind the development of CWT was to avail explicitly both magnitude and phase information. At the first level, for low level feature extraction, the dual tree complex wavelet transform will be used for both texture and color-based features. At the second level, to extract semantic concepts, we will group medical images with the use of one against all support vector machines. We are used here Euclidean distance for to measure the similarity between database features and query features. Also we can use a correlation-based distance metric for comparison of SVM distances vectors. The proposed approach has superior retrieval performance over the existing linear feature combining techniques.

Keywords

Content Based Image Retrieval system, Dual Tree complex Wavelet Transform, Support Vector Machines

1. 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. Comprehensive survey of existing CBIR techniques can be found in [9, 11].

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.

Kingsbury [16] proposed a new complex wavelet transform which allows fast computing Gabor like wavelets. Peter and Kingsbury [14] in their paper have shown how one can use this new transform to speed up and enhance the image. Kokare et al. [6] have proposed even better extension of this work. We can enhance the texture extraction capabilities of CWT for color image retrieval. 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.

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 [10].

2. FEATURE EXTRACTION

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 CBIR 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 CBIR. 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 (CWT) 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.

2.1 MEDICAL IMAGE DATABASE

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 (2.1). 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.

Figure 2.1 computed tomography (CT) images

2.2 DUAL TREE COMPLEX WAVELET TRANSFORM

Wavelets are being used in many different areas like signal denoising, image, audio and video compression, image smoothing and differential equation solution are active research topics. Wavelets offer some advantages as a tool for image processing, such as the multiresolution formulation, which allows the reduction of computational complexity. Kingsbury's [16] dual tree complex wavelet transform (CWT) is an enhancement to the discrete wavelet transform (DWT), with important additional properties. The main advantages, as compared to the DWT, are that the complex wavelets are approximately shift invariant and that the complex wavelets have separate sub-bands for positive and negative orientations. Conventional separable real wavelets only have sub-bands for three different orientations at each level, and cannot distinguish between lines at 45◦ and −45◦ respectively. The complex wavelet transform attains these properties by replacing the tree structure of the conventional wavelet transform with a dual tree. At each scale one tree produces the real part of the complex wavelet coefficients, while the other one produces the imaginary parts. A complex-valued wavelet $\psi(t)$ can be obtained as:

$$\psi(t) = \psi h(t) + j\psi g(t) \tag{1}$$

Where $\psi h(t)$ and $\psi g(t)$ are both real valued wavelets. CWT like Gabor transform has six orientations at each of four scales. The main advantage, as compared to the Gabor transform, is speed of computation. It has a redundancy of only 4 in 2-dimensions and so the post- processing stages (of calculating mean and standard deviations) are also faster as it has less redundancy than the Gabor wavelets. One can see more details related to orientation and scales. Each row represents one scale and the columns represent angles within that scale.

The four scale decomposed image by using DWT then that provide three directional filter that angles are 0, 45, 90 degree. While decomposed by using DTCWT then provide six directional filters that angles are ±15, ±45, and ±75 degree.

3. SUPPORT VECTOR MACHINES

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 [12]. It is being used in many application areas such as character recognition, image classification, bioinformatics, face detection, financial time series prediction etc.

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 hyperplane W. X+b = 0, where w and b are slope and intersection.

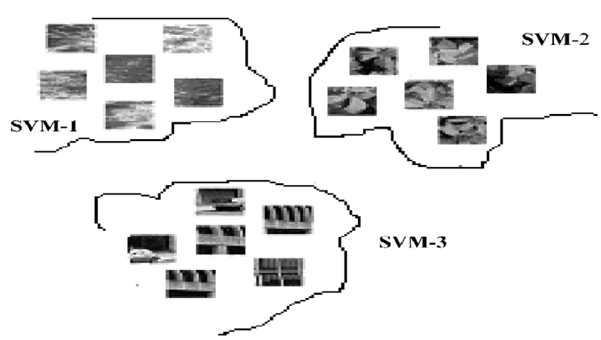

Figure 3.1. One against all classification showing three support vector machines.

SVM usually incorporates kernel functions for mapping of non-linearly separable input space to a higher dimension linearly separable space. Many kernel functions exist such as radial bases functions (RBF), Gaussian, linear, sigmoid etc. 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.

4. CWT AND SVM BASED IMAGE RETRIEVAL

In this chapter, we describe the structure of the proposed SVMBIR system in detail. Figure 4.1 shows the main components of the proposed system and the control flows among them. The following steps show the detail of our proposed algorithm:

Step 1: Features are extracted from each image using complex wavelet transform. So we got 24 real and 24 imaginary detailed sub-bands, and 2 real and 2 imaginary approximation sub-bands. We got 26 sub-bands. To calculate the features we measured the mean and standard deviation of the magnitude of the transform coefficients in each of 26 sub-bands. These features were then stored in feature database for later comparison.

Step 2: From each class of images included in the image database some typical images (*K*) were selected for training of support vector machine for that class. Selection of these training images can be done randomly or from a sequence. In our experiments we used first *K* images for training. We used one against all training method as it is the best when one needs good speed and reliable performance. This is done using *trainlssvm* function of LSSVM. We used 'RBF' as kernel function for training of support vector machines. Optimal parameter selection is always a bottleneck of support vector machines. LSSVM provides a function *tunelssvm* which can be used for stimation of optimal parameters. We used grid search approach for searching optimal parameters.

Step 3: The distance of each image included in the database from each trained SVM is calculated. This is done using simlssvm function of LSSVM. Each of this distance is grouped in the form of distance vectors. This distance vector will store distance of each image from each support vector machine. Finally, we store all these distance vectors in distance vectors database. Steps 1 – 3 are done offline and after these steps our system is ready to process the user queries.

Step 4: When the user gives the system a query image, features from the query image are extracted. Using this feature vector of query image distance vector of query image is calculated.

Step 5: Query image feature vector is compared with all the feature vectors included in the respective class in database. The Euclidean distance metric can be used for this comparison.

$$D=\sqrt{\sum_{i=1}^{n} |xi - yi|2} \qquad (2)$$

In this case, *xi* is the query image feature vector and *yi* is the feature vector of images included in the database. n varies from 1 . . . N, where N is the total number of images included in the image database.

Step 6: Finally, the top Q images having minimum distance are retrieved and presented to the user.

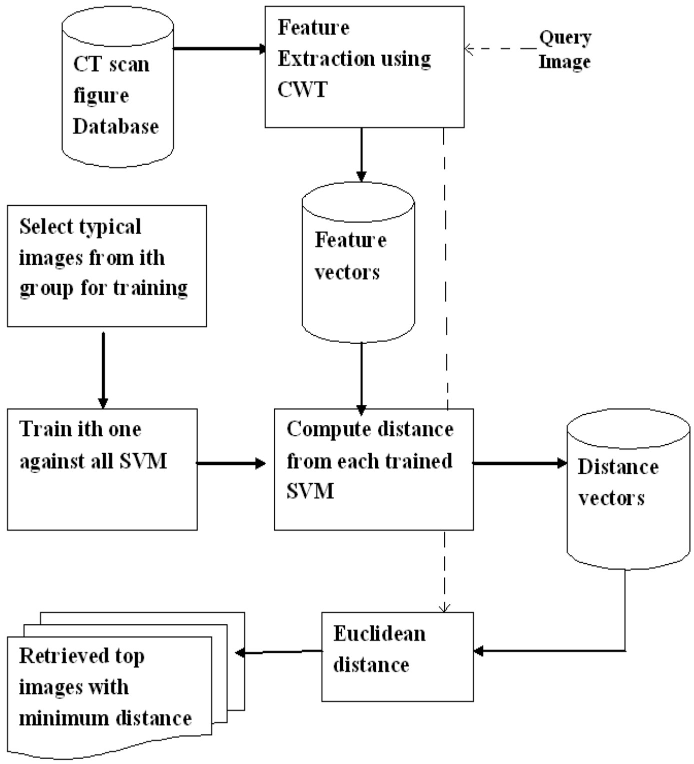

Figure 4.1. The structure of the proposed SVMBIR system

5. APPLICATIONS

These systems are being used mainly for the following application areas : Security, Intellectual Property, Brand protection, Military, Architectural and engineering design, Fashion and interior design, Journalism and advertising, Medical diagnosis, Education and training, Home entertainment, Web searching.

6. CONCLUSION

The proposed system is based on the observation that the images users need are often similar to a set of images with the same conception instead of one query image and the assumption that there is a nonlinear relationship between different features. We used complex wavelet transform for feature extraction due directionality property. SVM is used for classification.CWT with SVM retrieval system gives better Precision and minimum Error rate.

7. EXPERIMENTAL RESULTS

In this section we have shown some experimental results to evaluate the performance of our proposed system. The image data set used in the experiments contains 120 medical images. These images are organized as having 20 images for each class there are six classes. We then count how many of these belong to the correct class (up to a maximum of 20) and define the retrieval rate as this number divided by 20.

Fig. 7.1 and Fig. 7.2 show the retrieved results of the proposed SVMBIR system, in which the first image is the query image. We can see from these figures that the proposed system is very efficient as set of images with same conception can be retrieved.

The performance parameter of proposed system are Precision i.e. retrieval efficiency or accuracy and Error rate. Compared with DWT, only CWT and combined CWT with SVM results are shown in table no.1. This system gives better retrieval efficiency than DWT and only CWT also error rate is minimized than other methods.

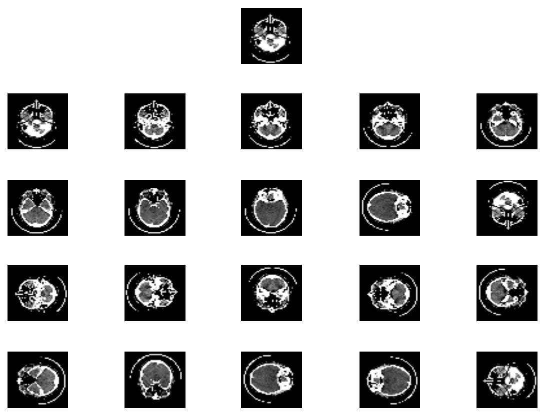

Figure (7.1) Retrieved results of SVM for Query image (01.jpg) from class1

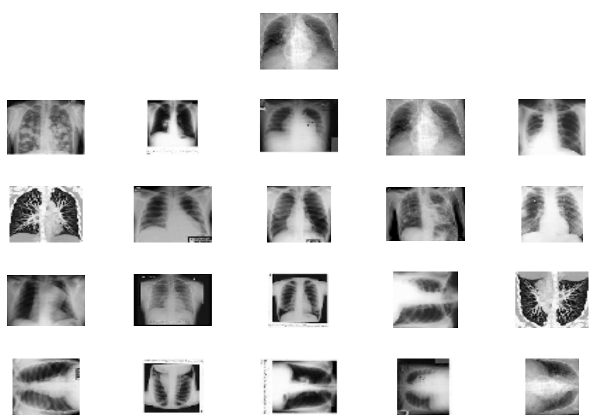

Figure (7.2) Retrieved results of SVM for Query image (024.jpg) from class2

Table (1): Performance of retrieval system compared using Precision and Error rate

Class/no. of images	Query Image No.	Method of feature extraction	No. of images retrieved	Relevant images retrieved	Precision/ retrieval efficiency	Error rate
Class 1 (Brain images) 1 to 20	01.jpg	DWT	21	20	0.95	0.05
		CWT	20	20	1	0
		CWT &SVM	**4**	**4**	**1**	**0**
Class 2 (heart images) 21 to 40	024.jpg	DWT	44	14	0.31	0.68
		CWT	24	13	0.56	0.38
		CWT &SVM	**11**	**8**	**0.72**	**0.54**
Class 3 (hand images) 41 to 60	043.jpg	DWT	52	5	0.09	0.9
		CWT	21	3	0.14	0.85
		CWT &SVM	**5**	**5**	**1**	**0**
Class 4 (whole heart images) 61 to 80	068.jpg	DWT	32	15	0.47	0.48
		CWT	16	11	0.68	0.31
		CWT &SVM	**16**	**10**	**0.63**	**0.37**
Class 5 (chest images) 81 to 100	082.jpg	DWT	38	18	0.47	0.52
		CWT	16	9	0.56	0.43
		CWT &SVM	**20**	**16**	**0.8**	**0.2**
Class 6 (leg Images) 101 to 120	0101.jpg	DWT	52	11	0.21	0.78
		CWT	17	5	0.29	0.7
		CWT &SVM	**6**	**4**	**0.67**	**0.33**

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