Certain Improvements in Hybrid Feature Extraction Methods for Medical Image Classification

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Abstract : Content Based Image Retrieval is a technique which uses visual contents for searching images from large scale image databases Information extracted from images such as color, texture and shape are known as feature vectors. Using multiple feature vectors to describe an image during retrieval process increases the accuracy when compared to the retrieval using single feature vector. The objective of this paper is to analyze the performance of coif let wavelet and Moment Invariant (MI) feature extraction methods and to evaluate the classification accuracy using Support Vector Machines (SVM) with Radial Basis Function kernel (RBF). Experiments were conducted on CT scan images of head, lung and stomach and the performance is investigated.

Keywords: Coiflet wavelet, Content Based Image Retrieval (CBIR), Feature Extraction (FE), Moment Invariant (MI), Computed Tomography (CT), Support Vector Machines (SVM), Radial Basis Function kernel (RBF) Similiarity Measurement (SM).

1 Introduction

The rapid expansion of the Internet and the wide use of digital data have increased the need for both efficient image database creation and retrieval procedure. The challenge in image retrieval is to develop methods that can extract the important characteristics of an image, which makes it unique, and allow its accurate identification. With extensive digitization of images, diagrams/paintings, traditional keyword based search was inefficient for required data retrieval. CBIR has wide applications in medicine as it aids doctors to make better decisions. Various methods were in research for CBIR with low level image features like color layout, histogram, texture/analysis of images in frequency domain including Fast Fourier Transform (FFT) and Wavelets. The CBIR system performs two major tasks and is shown in Fig. 1.

Feature extraction (FE): A set of features called image signature or feature vector, is generated to accurately represent the content of each image in the database.
A feature vector is greatly smaller in size than the original image.

Similarity measurement (SM): A distance between the query images is computed and in each image the database using their signatures is considered so that the top “closest” images can be retrieved [4].

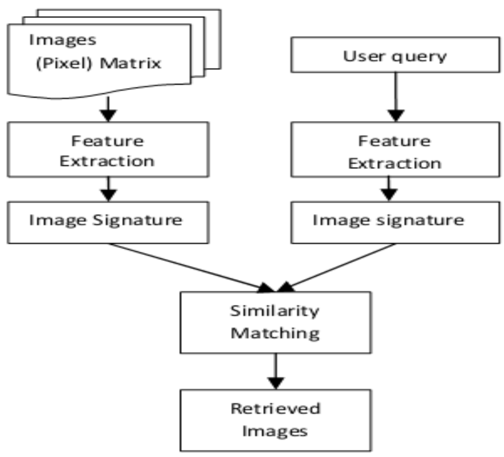

Fig.1 CBIR

Similarly, classification algorithms like Naïve Bayes classifier, SVM, Decision tree induction algorithms and Neural Network (NN) based classifiers were studied extensively. Ingrid Daubechies et al [3] designed Coiflets which are discrete wavelets having scaling functions with vanishing moments and showed better performance in this area than others due to multilevel decomposition with variable trade-off in time and frequency resolution. Time-frequency wavelet representation is done through repeated signal filtering with a pair of filters halving the frequency domain in the middle. Moments can provide characteristics of an object that uniquely represent its shape. Invariant shape recognition is performed by classification in the multidimensional moment invariant feature space.

In this paper, features are extracted from the medical images using Coif let wavelets; Moment Invariants and classification accuracy of retrieval is evaluated using Naïve Bayes and Support Vector Machine. The rest of the study is organized as follows: Section 2 reviews some of the studies available in the literature. Section 3 details the methodology, Section 4 reports the results and section 5 concludes the study.

2 Related Works

Ardizzoni et al, [1] presented WINDSURF (Wavelet-Based Indexing of Images Using Region Fragmentation), a new approach to content-based image retrieval. Wavelet transform methods extract color/texture features from images applying clustering techniques to partition image into "homogeneous" regions sets. Images similarity was assessed using Bhattacharyya distance for comparison of region descriptors and combining image level results. Experiments on a test bed of 10,000 general-purpose images revealed that the proposed approach is effective image retrieval when they are "semantically" similar to query images. In particular, the results of WINDSURF was compared with the approach by Stricker and Orengo [9], showed that a significant improvement was obtained in the quality of the result.

Feature Extraction algorithm is a very important component of any retrieval scheme. Kundu et al, [5] was proposed M-band Wavelet Transform based feature extraction algorithm. The MxM sub-bands were used as primitive features, over which energies computed in a neighborhood are taken as the features for each pixel of the image. These features were clustered using FCM to obtain image signature for similarity matching using the Earth Mover's Distance. The results obtained were compared with MPEG-7 content descriptor based system and found to be superior.

Patil et al [8] demonstrated a novel approach for shift invariant image retrieval using set of dual-tree discrete wavelet transform (DT-DWT) and dual-tree complex wavelet transform (DT-CWT). The DT-CWT is relatively recent enhancement to the DT-DWT. It is nearly shift invariant and directionally selective in two and higher dimensions. The two dimensional DT-CWT is no separable, but it is based on a computationally efficient, separable filter banks (FB). The magnitude and phase of CWT coefficients can be exploited in the development of the new efficient and effective wavelet based algorithms where DWT is inefficient.

Liu, et al., [10] developed a novel texture feature, based on SVM termed texture correlogram, and useful for high-level image classification. To solve binary classification drawbacks initially, SVM classifier frame is used. A novel technique was developed using a hierarchical structure to deal with the training data set's multiple classes. Texture correlogram is framed to attain spatial distribution information. The proposed classification and texture features are more efficient/ effective than the other existing methods for high level classification. The proposed method achieves improved classification accuracy and an additional benefit is SVM classification tree's hierarchical structure reveals interclass relationships. This can be further used to explore relationships among high-level concepts.

Based on single feature image retrieving techniques study - which includes color clustering, color texture and shape - a new retrieving process with multi-feature fusion/relevance feedback was suggested by Xia et al [11] to retrieve endoscopic images. A prototype evaluated the proposed method's performance and evaluation parameters like retrieval precision/recall, statistical average position of top five most similar images on various features. An algorithm having multi-features fusion/relevance feedback ensures accurate/quicker retrieving capability than one with single feature image retrieving technique. This was because of its flexible feature combination/interactive relevance feedback.

Problem of texture and shape feature extraction was focused by Arun & Menon [2]. A new approach combining rotation invariant contourlet transform and Fourier descriptors successfully is proposed. Rotation invariant contourlet transform was used to extracts the texture features and Fourier descriptor extracts shape features. This method's retrieval performance was tested with a large medical image database and measured with common performance measurements.

3 Methodologies

The performance of an image classification system depends on the feature extraction technique, feature selection technique and the classification algorithm used. The feature extraction technique should be capable of extracting features such that variations in either scaling or rotation of the feature in the spatial domain do not affect the classification algorithm. This is difficult to achieve in the spatial domain due to the inherent character of images. However wavelet transforms have been able to achieve this property by truncating high frequency components and capturing information of low frequency components at different resolution scales.

Since medical images obtained from different part of the body has distinctive shapes, this work proposed to use features obtained from Moment Invariants which are extremely reliable in finding shape vectors and Wavelet. Coiflet was used to extract the energy coefficients because of the orthogonal property displayed by this wavelet leading to a shorter filter with N/3 vanishing moments. The features extracted were classified using SVM for their efficacy. Figure 2 shows the flowchart of the proposed methodology used in this study. The methods used are explained in detail in the following sections.

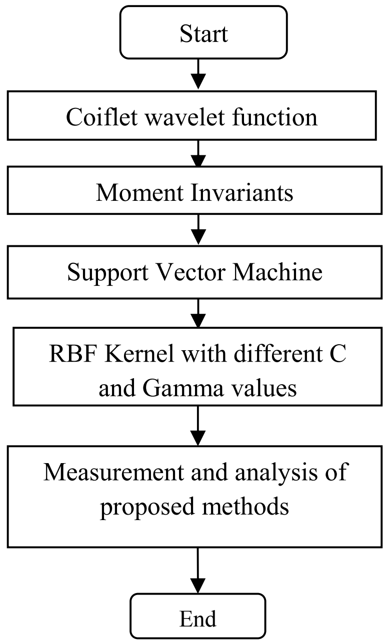

Fig.2 Flowchart of proposed system

3.1 Coiflet Wavelet Function

Coiflet wavelets are near symmetric with the wavelet functions have N/3 vanishing moments and N/3-1 scaling functions.In Coif let wavelet function, there are 2N moments equal to 0 and the scaling function has 2N-1 moments equal to 0. The above two functions have a support of length 6N-1. Both daubechies and coiflets wavelet families have an orthogonal and bi-orthogonal properties. Coiflet wavelet family is shown in following Figure 3 [2]

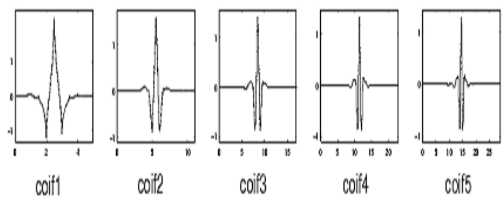

Fig. 3 Coiflet Wavelet Families

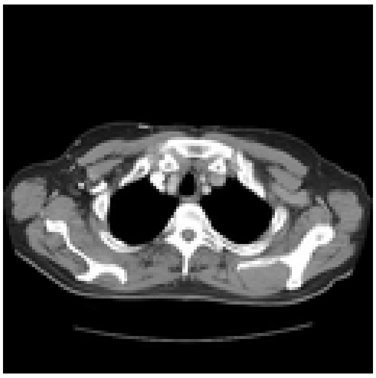

Fig. 4 Lung CT scan

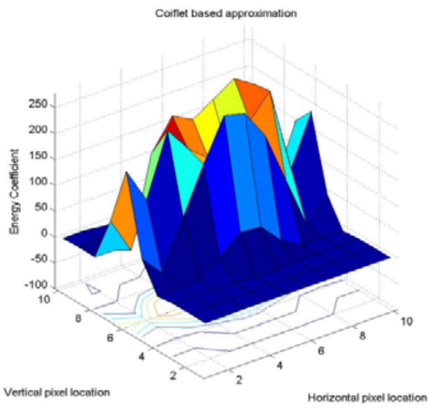

Fig. 5 Coiflet based approximation

3.2 Moment Invariants

MIs have been frequently used as features for image processing, remote sensing, shape recognition and classification. Moments can provide characteristics of an object that uniquely represent its shape. Invariant shape recognition is performed by classification in the multidimensional moment invariant feature space. Several techniques have been developed that derive invariant features from moments for object recognition and representation. Traditionally, MIs are computed based on the information provided by both the shape boundary and its interior region. The moments used to construct the moment invariants are defined in the continuous but for practical implementation they are computed in the discrete form. Given a function *f(x, y)*, these regular moments are defined [6] by:

$$M_{pq} = \iint x^p y^q f(x, y) dxdy \qquad (1)$$

M_{pq} is the two-dimensional moment of the function *f(x,y)*. The order of the moment is (p + q) where p and q are both natural numbers. For implementation in digital form this becomes:

$$M_{pq} = \sum_x \sum_y x^p y^q f(x, y) \qquad (2)$$

MIs have been frequently used as features for the shape recognition. They get computed based on the information provided by both shape boundary and its interior region. The properties of moment receive considerable attention in recent years.

3.2 Support Vector Machine

Also SVMs are a class of supervised learning algorithms that can be created as an extension to nonlinear models of the generalized portrait algorithm developed by Vladimir Vapnik, for classification in a multidimensional parameter space. These algorithms are based on the concept of decision planes for classifying objects by using their relative positions in the n-dimensional parameter space. A large number of observed properties are analyzed simultaneously by the classifier making the data usage as full. Within the full parameter space, it is possible to build a more reliable classifier. Again, the method requires a Training Sample, that is, asset of data that have known classifications. Generally, SVM algorithms are sensitive for the measurement errors and are used as limited for extracting information from noisy data sets.

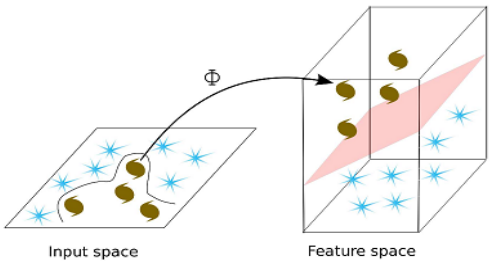

Fig. 6 Operation of the SVM algorithm

The input data (on the left side) are transformed by a kernel into the higher dimensional feature space (right side). Here, instead of having a complex boundary separating different classes of objects, an optimal separating hyper plane can be found [7].

Given a training set of $(x_i, y_i), i1,2,....l$ where $x_i \in R^n$ and $y \in \{1,-1\}^l$

SVM solves the optimization problem of:

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \quad \text{Subject to}$$

$$y_i \left(w^T \phi(x_i) + b \right) \geq 1 - \xi_i \text{ and } \xi_i \geq 0 . \qquad (3)$$

The function ϕ maps the vectors x_i in higher dimensional space. C>0 is penalty parameter of the error term. Lagrangian method is used to solve the optimization model, which is similar to the method for solving optimization problems in a separable case. The dual variables Lagrangian is maximized as follows:

$$\underset{\alpha}{Max} \;\; L_D(\alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{m} \alpha_i \alpha_j y_i y_j \left\langle x_i . x_j \right\rangle \qquad (4)$$

Subject to: $0 \leq \alpha_i \leq C \;\; i = 1,..,m$ and $\sum_{i=1}^{m} \alpha_i y_i = 0$ (5)

To compute the optimal hyper plane, a dual Lagrangian LD(α) is maximized as regards non-negative α_i subject to constraints

$$\sum\nolimits_{i=1}^{m} \alpha_i y_i = 0 \text{ and } 0 \leq \alpha_i \leq C \qquad (6)$$

The penalty parameter C, now the upper bound on α_i, is user determined. A kernel function is defined as $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ (7)

The Radial Basis function is given as follows:

$$K(x_i, x_j) = \exp\left(-\gamma \left\| x_i - x_j \right\|^2 \right) \;\; , \gamma > 0 \qquad (8)$$

Proper parameter setting in the kernels increases SVM classification accuracy. There are two parameters to be determined in the SVM model with the RBF kernel: C and gamma (γ). The gamma parameter automatically defines the distance which a single training example can reach, with low values meaning ‘far’ and high values meaning ‘close’. The C parameter gives the trade-off of training examples misclassification against decision surface simplicity. Lower C values ensure a smooth decision surface while higher C values attempts to classify training examples accurately. Experiments are carried out to evaluate SVM performance through variations of the Gamma and C parameters.

4 Results and Discussion

Experiments were conducted using 520 CT scans images of 4 classes. The images were obtained from National Biomedical Imaging Archive. Features were extracted using Coif let wavelet and Moment Invariant. Experiments were for SVM-RBF was conducted with various C and Gamma values. All the experiments were conducted for 10-fold cross validation. Features from Coiflet and MI were fused using the proposed product rule fusion technique after obtaining the Median Absolute Deviation (MAD) between the two features. The classification accuracy and the root mean square error (RMSE) achieved are better when compared with the result of 150 images of brain, chest and colon [10].

The classification accuracy and the root mean square error (RMSE) achieved for Naïve Bayes and SVM is tabulated in Table 1. Figure 7 shows the classification accuracy.

Classifiers	Classification Accuracy		
	Coiflet	MI	Coiflet and MI
Naïve Bayes	90	84	91.33
SVM - Polykernel	87.33	80.67	88.36
SVM-RBF C=1, γ =0.1	88	80.67	89.33
SVM-RBF C=1,γ=0.05	81.33	78.67	82.67
SVM-RBF C=0.5,γ= 0.5	84.67	84.67	86

Table 1 Classification accuracy for Naive Bayes, SVM and SVM-RBF

From table 1 and figure 7, it is observed that the classification accuracy of proposed Coiflet and MI method increases by 1.48 % than Coiflet and increases by 8.73 % than MI with naïve Bayes classifier. The classification accuracy of proposed Coiflet and MI method increases by 1.18 % than Coiflet and increases by 9.53 % than MI with SVM Polykernel classifier. Table 2 and Figure 8 show the RMSE.

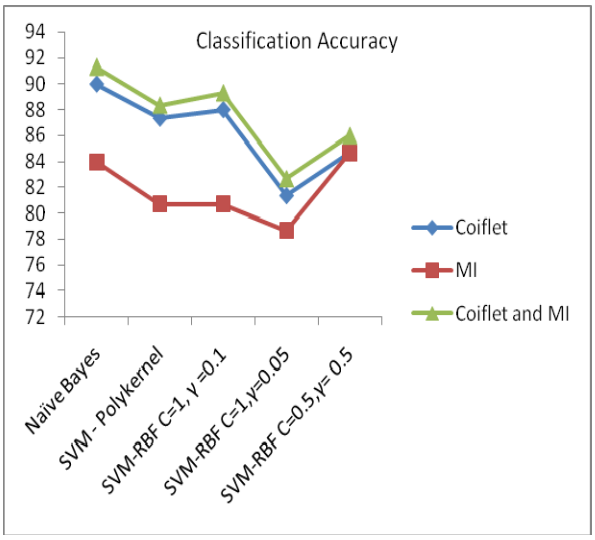

Fig. 7 Classification Accuracy for Naive Bayes, SVM and SVM-RBF

From table 2 and figure 8, it is observed that the RMSE of proposed Coiflet and MI method decreases by 13.01 % than Coiflet and decreases by 38.09 % than MI with naïve Bayes classifier. The RMSE of proposed Coiflet and MI method decreases by 5.98 % than Coiflet and decreases by 25.53 % than MI with SVM Polykernel classifier

Classifiers	RMSE		
	Coiflet	MI	Coiflet and MI
Naïve Bayes	0.2582	0.3628	0.2246
SVM - Polykernel	0.2942	0.3714	0.2766
SVM-RBF C=1, γ =0.1	0.2905	0.3746	0.2714
SVM-RBF C=1,γ=0.05	0.3749	0.3844	0.3251
SVM-RBF C=0.5,γ= 0.5	0.3255	0.3517	0.3177

Table 2 RMSE for Naive Bayes, SVM and SVM-RBF

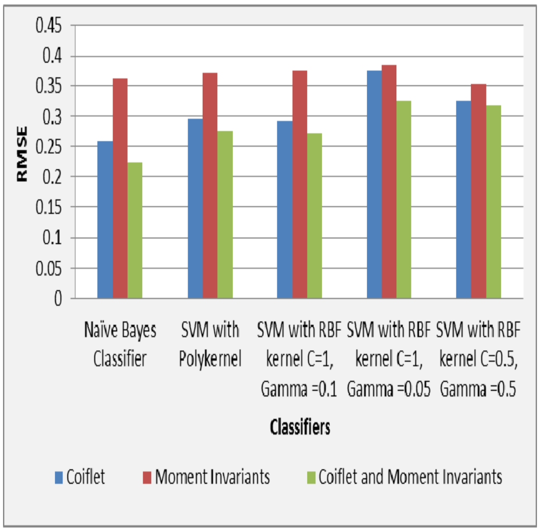

Fig. 8 RMSE for Naive Bayes, SVM and SVM-RBF

5 Conclusion

In this study, a method of classification of CT images is presented. Features were extracted using Coiflet wavelet. All the experiments were conducted for 10-fold cross validation. Experimental results show that the varying of the parameter C and Gamma has a significant effect on the classification accuracy and the RMSE. Naïve Bayes achieves the best classification of 91.33%. Further work is required by optimization of the SVM to improve classification accuracy.

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