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Research Article

An Evolutionary Algorithm for Enhanced Magnetic Resonance Imaging Classification

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Abstract: This study presents an image classification method for retrieval of images from a multi-varied MRI database. With the development of sophisticated medical imaging technology which helps doctors in diagnosis, medical image databases contain a huge amount of digital images. Magnetic Resonance Imaging (MRI) is a widely used imaging technique which picks signals from a body's magnetic particles spinning to magnetic tune and through a computer converts scanned data into pictures of internal organs. Image processing techniques are required to analyze medical images and retrieve it from database. The proposed framework extracts features using Moment Invariants (MI) and Wavelet Packet Tree (WPT). Extracted features are reduced using Correlation based Feature Selection (CFS) and a CFS with cuckoo search algorithm is proposed. Naïve Bayes and K-Nearest Neighbor (KNN) classify the selected features. National Biomedical Imaging Archive (NBIA) dataset including colon, brain and chest is used to evaluate the framework.

Keywords: Correlation based Feature Selection (CFS), Magnetic Resonance Imaging (MRI), Naïve Bayes K-Nearest Neighbour (KNN), National Biomedical Imaging Archive (NBIA) dataset

INTRODUCTION

Medical image database used for image classification/teaching contains images of various modalities. Many of the imaging categorization systems automatically classify images and related information in medical datasets. IBM introduced Interactive Life sciences imaging visualization and exploration (I Live) system (Mojsilove and Ciomes, 2002) developed for automatic medical images categorization based on modalities. It is based on visual features semantical set and their relevance. Hence, its organization is based on capturing various imaging modalities semantics.

Textual annotation interpretation based modality categorization in medical imaging was proposed in Florea *et al*. (2005). A rule-based medical image modality categorization approach was suggested. To determine medical image modality, textual annotation was based on a radiologist based set of 96 production rules. Malik and Zremic (2005) categorized imaging modalities with image size, bits number per pixel, number of rows and columns, dimensionality and input images color information. Information derived was compared with the lookup table data. Further, low level global/local features are extracted to classify images to a narrower imaging modalities group. Imaging modalities like X-Ray, Ultrasound and Magnetic Resonance Imaging (MRI) have differences in gray scale contrast. Hence, gray scale contrast information, boundaries, regions color composition and frequency information are considered low level features.

An image classification system, pre-processes the medical images, extracts features from the image and classifies the feature. Texture is widely used as features and texture classification assigns an unknown sample image to one of known texture classes set. Texture classification is a main domain in texture analysis and is important in many computer image analysis applications for images classification/segmentation based on local spatial variations of intensity/color. Successful classification/segmentation requires efficient image texture (Kassner and Thornhill, 2010) description.

The feature set extracted is generally high dimensional. Classifiers performance deteriorates due to irrelevant features in the feature set. Thus, feature selection is applied to reduce the number of features and to remove irrelevant features. The feature selection process improves the performance of the classifier. Classification predicts group membership for data instances. Data mining includes use of sophisticated data analysis tools to discover relationships in large data sets. Data mining is not managing data but also includes data analysis/prediction.

In this study, an image classification method is presented for image retrieval from a multi-varied MRI database. The proposed framework extracts features using Moment Invariants (MI) and Wavelet Packet Tree (WPT) from the MRI images. The extracted features set

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is reduced using Correlation based Feature Selection (CFS). A CFS based feature selection with cuckoo search algorithm is proposed. Naïve Bayes (NB) and K-Nearest Neighbor (KNN) classify features. NBIA Dataset with colon, brain and chest is used to evaluate the framework.

LITERATURE REVIEW

A feature ranking based nested Support Vector Machine (SVM) ensemble for medical image classification was proposed by Varol *et al*. (2012) where a brain structural MRI method was presented. A SVM ensemble classifies a subject as patient or normal control. Image voxels are ranked on voxel wise t-statistics between voxel intensity values and class labels. Voxel subsets selection is based on rank value using forward feature selection scheme. A SVM classifier was finally trained on every image voxels subset. The method was used to classify patients with neurological diseases like Alzheimer's disease and autism spectrum disorder.

Cascading Genetic Algorithm (GA) and CFS for feature subset selection in medical data mining was proposed by Karegowda and Jayaram (2009). In the first stage of proposed method, GA and CFS were used in a cascaded procedure. GA rendered global search of attributes with fitness evaluation effected by CFS. The second stage fine-tuned classification using Neural Network (NN) by making feature subset elicited in first stage network inputs. Experiments signified that feature subset identified by the new filter when provided as input to back propagation NN classifier leads to improved classification accuracy.

Feature selection/classification of breast cancer on dynamic MRI using ANN was introduced by Keivanfard *et al*. (2010) where new feature selection/classification methods based on NN are applied to classify breast cancer on dynamic MRI. The database including benign and malignant lesions is specified to select and classify features through the proposed methods. It was collected between 2004 and 2006. A forward selection method locates best classification features. Also, ANN like Multilayer Preceptron (MLP) NN, Probabilistic NN (PNN) and Generalized Regression NN (GRNN) are applied to classify breast cancer into 2 groups; benign and malignant. Training and recalling NN were got from considering 4-fold cross validation.

Texture-based continuous probabilistic framework for medical image representation and classification was introduced by Lederman (2012) which addressed the problem of medical image representation and classification. Image classification was performed using a parallel Gaussian Mixture Models (GMMs) framework composed of many GMMs, schematically connected in parallel, where each GMM represents a different imaging angle. Results showed the approach could efficiently/reliably represent/classify medical images acquired in various procedures.

Efficient feature selection based on ICA was proposed by Prasad *et al*. (2004) where authors introduced a new dimensionality reduction approach for feature space employing ICA. In applications, ICA resulted in smaller number of effective features than relief attribute estimator and it usually outperformed both relief attribute estimator and CFS, when used as Naïve Bayes and instance based learning and decision trees pre-processing step. Also, by disregarding some features, it was proved in some cases that the ICA is more accurate than all three features based classification. Also, decision trees from pre-processed data are often smaller than those from original feature space.

A combined statistical and model based texture features to improve image classification was proposed by Al-Kadi (2008) which aims to improve texture classification accuracy based on extracting texture features using 5 different texture measures and classifying patterns using a naive Bayesian classifier. Three statistical-based and 2 model-based methods extracted texture features from 8 texture images and ranked their accuracy after using each method individually and in pairs. Accuracy improved up to 97.01% when model based-Gaussian Markov Random Field (GMRF) and Fractional Brownian Motion (FBM)-were combined for classification compared to highest achieved using each of five different methods singly. They proved to be better in classification compared to statistical methods. Use of GMRF with statistical based methods like Grey Level Co-occurrence Matrix (GLCM) and Run-Length Matrix (RLM), improved overall accuracy to 96.94 and 96.55%, respectively.

Automatic retrieval of MRI brain image using multi-queries system was introduced by Mohanapriya and Vadivel (2013). This proposed retrieval using a supervised classifier which concentrates on extracted features. GLCM algorithm extracts texture features from images. Feature optimization is undertaken on extracted features to select best features to train a classifier. Classification is performed on a dataset and classified into 3 categories like normal, benign and malignant. Query image was classified by classifier to a specific class and relevant images were retrieved from the database.

Feature extraction for object recognition using PCA-KNN with application to medical image analysis was proposed by Kamencay *et al*. (2013). The proposed method is divided into 3 steps. The first is based on feature extraction from input images using Scale Invariant Feature Transform (SIFT) descriptor. Each feature is represented using one/more feature descriptors. In medical systems images used as patterns are represented by feature vectors. In the second step, Eigen values and Eigen vectors are extracted from images. PCA algorithm is applied after reducing the features number by SIFT algorithm. The goal is extracting important information as a set of new orthogonal variables called principal components. In the final step, a nearest neighbor classifier classified images based on extracted features.

METHODOLOGY

This study aims to classify MRI colon, brain and chest images. Feature extraction is through using Moment Invariants (MI) and Wavelet Packet Tree (WPT) in the proposed framework and extracted features are reduced using CFS and proposed CFS with cuckoo search algorithm. Naïve Bayes and KNN classify the selected features. NBIA dataset of colon, brain and chest is used to evaluate the framework.

NBIA dataset: The National Biomedical Imaging Archive is a searchable, national repository integrates in vivo cancer images with clinical/genomic data. NBIA provides the scientific community with access to DICOM images, annotations, image markup and metadata. Processed multiple MRI sequences were downloaded from \RIDER Neuro MRI" collection at http://wiki.nci.nih.gov/ display/CIP/RIDER (Whitcher *et al*., 2011).

Moment Invariants (MI): MI is used as features for shape recognition and its computation is based on information from shape boundary and its interior region. Though many fast algorithms to compute traditional MI were proposed, none ever showed theoretical results of MIs computed based on shape boundary only (Chen, 1993). Let f (x, y) be over a closed and bounded region R and 0 otherwise. Define the (p, q)th moment as:

$$m_{pq} = \iint x^p y^q f(x,y)dxdy, for\ p,q = 0,1,2\ .\ .\ .\ .\ . \tag{1}$$

The central moments are expressed as:

$$\mu_{pq} = \iint x^p y^q f(x,y)\,dx\,dy \tag{2}$$

where,

$$\bar{x} = \frac{m_{10}}{m_{00}}, \quad \bar{y} = \frac{m_{01}}{m_{00}} \tag{3}$$

For digital images:

$$\mu_{pq} = \sum_{(x,y)/R}\sum (x-\bar{x})^p (y-\bar{y})^{pq} \tag{4}$$

It is verified that central moments to the order p+q<3 may be computed by following formulas:

$$\mu_{00} = m_{00}, \mu_{11} = m_{11} - \bar{y}m_{10} \tag{5}$$

$$\mu_{10} = 0, \mu_{30} = m_{30} - 3\bar{x}m_{20} + 2\bar{x}^2 m_{10} \tag{6}$$

$$\mu_{01} = 0, \mu_{12} = m_{12} - 2\bar{y}m_{11} - \bar{x}m_{02} + 2\bar{x}^2 m_{10} \tag{7}$$

$$\mu_{20} = m_{20} - xm_{10} \tag{8}$$

$$\mu_{21} = m_{21} - 2xm_{11} - ym_{20} + 2\bar{x}^2 m_{01} \tag{9}$$

Central moments are translation invariant. They can be normalized to be invariant to scaling change by the formula. Equation quantities are called normalized central moments:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}\gamma}$$

where,

$$\gamma = \frac{p+q}{2} + 1 \tag{10}$$

For p+q = 2, 3 …

Wavelet Packet Tree (WPT): Wavelet packet method is a generalization of wavelet decomposition offering a range of signal analysis possibilities. In wavelet analysis, a signal is split into approximation and detail. Approximation is then split into a second-level approximation and detail the process being repeated. For n-level decomposition, there are n+1 possible ways to decompose/encode a signal. In wavelet packet analysis, details and approximations are split yielding more ways to encode the signal. For e.g.; wavelet packet analysis allows signal S to be represented as A1+A6+D6+D3. This is an example of representation that impossible with ordinary wavelet analysis (Shinde, 2004). Wavelet decomposition tree is a part of such a complete binary tree. As stated above wavelet packet analysis is similar to DWT with the difference being that in addition to the decomposition of wavelet approximation component at every level, wavelet detail component also decomposes to get own approximation and detail components.

The WPT's every component is viewed as a filtered component with filter bandwidth decreasing with increasing decomposition and the whole tree being viewed as a filter bank. At tree top, wavelet packet components time resolution is good but at the expense of poor frequency resolution while at the bottom wavelet packet analysis ensures that frequency resolution of decomposed component with high frequency content is increased. Hence, wavelet packet analysis provides better frequency resolution control for signal decomposition (Chang and Kuo, 1993). A wavelet packet is represented as a function ψ where 'i' is modulation parameter, 'j' dilation parameter and 'k' translation parameter:

$$\psi^{i}_{j,k}\left(t\right)=2^{-\frac{j}{2}}\psi^{i}(2^{-j}t-k) \tag{11}$$

where, i = 1, 2…j_n and 'n' is wavelet packet tree decomposition level.

In this study, the features extracted from the MI and WPT are concatenated to form a fused feature vector.

Correlation-based Feature Selection (CFS): CFS is a popular method. It searches among features according to redundancy degree amongst them to locate a features subset highly correlated with class, yet uncorrelated with each other. Experiments on natural datasets revealed that CFS eliminated over half of features and classification accuracy with reduced feature set was equal to or better than accuracy using complete feature set (Hall, 1999).

If correlation amongst test components and outside variable is known and inter-correlation between each components pair is given, then correlation between a composite test of summed components and outside variable is predicted from:

$$r_{zc}=\frac{k\overline{r_{zi}}}{\sqrt{k+(k-1)\overline{r_{ii}}}} \tag{12}$$

where,
r_{zc} = Correlation between summed components and outside variable
k = Number of components
r_{zi} = Average of correlations between components and outside variable
r_{ii} = Average inter-correlation between components

Cuckoo search: Cuckoo Search is inspired by obligate brood parasitism of cuckoos which lay eggs in host bird's nests. Some cuckoos have evolved so that female parasitic cuckoos imitate colours/patterns of eggs of chosen host species reducing probability of eggs being abandoned and hence increasing their re-productivity. It is known that many host birds engage directly conflict with intruding cuckoos. In such cases, when host birds discover the eggs are not theirs, they are either thrown away or the nests are abandoned and new ones built elsewhere.

Also the egg-laying timing of some species is amazing. Parasitic cuckoos choose a nest where a host bird has just laid its eggs. Usually, cuckoo eggs hatch earlier than host eggs. When the first cuckoo chick hatches, its first instinct is to evict host eggs by blindly propelling them out of the nest thereby increasing the cuckoo chick's share of food provided by host bird. Studies reveal cuckoo chicks imitating the host chicks call to gain access to more feed.

Cuckoo search implemented as follows: Every egg in a nest is a solution with a cuckoo egg representing a new solution. The aim is to use new and potentially better solutions (cuckoos) to replace the nests not-so-good solutions. Simply put, each nest has one egg. The algorithm is extended to more complicated cases where each nest has many eggs representing a solutions set (Yang and Deb, 2009). Cuckoo Search is based on 3 rules:

- A cuckoo lays one egg at a time dumping it in a randomly chosen nest
- The best nests with high eggs quality (solutions) carry over to next generations
- Available host nests are fixed and a host can discover an alien egg with probability ⟦P⟧ ϵ (0, 1). In this case, the host bird either throws the egg out abandons the nest to build a new nest in a new location (Valian *et al*., 2011)

RESULTS AND DISCUSSION

In the proposed framework, the features are extracted using Moment Invariants and Wavelet packet tree. The features of MI and WPT are concatenated to form a fused feature vector. The extracted features sets are reduced using CFS and Proposed CFS with cuckoo search algorithm. NB and KNN used for classification of the features. NBIA Dataset consisting of colon, brain, chest is used for evaluating the framework. The results obtained are as shown in Fig. 1 to 5.

From Fig. 1 it is shown that the KNN classifier classifying the fused vectors with proposed CFS based feature selection method shows higher classification accuracy than the other methods. The KNN achieves 6.85% better classification accuracy than the NB. It is also seen that the proposed cuckoo based feature selection improves the classifiers accuracy by 2.1 to 6.98%.

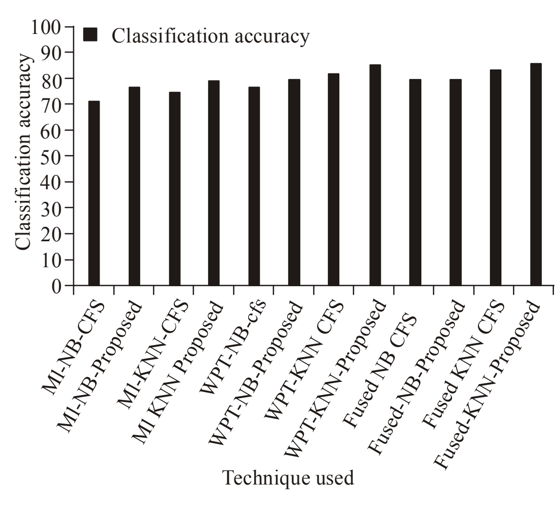

Fig. 1: Classification accuracy

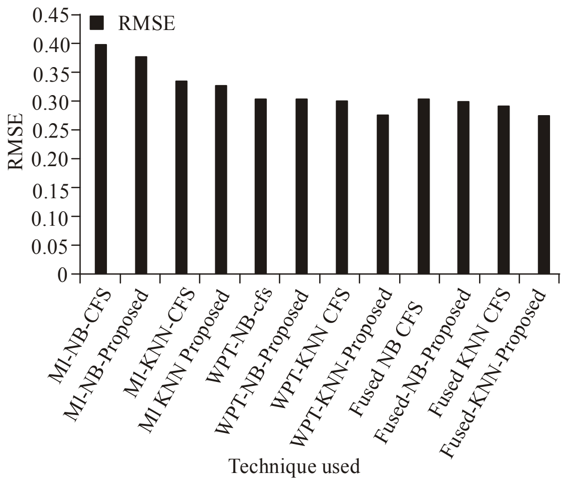

Fig. 2: Root mean square error

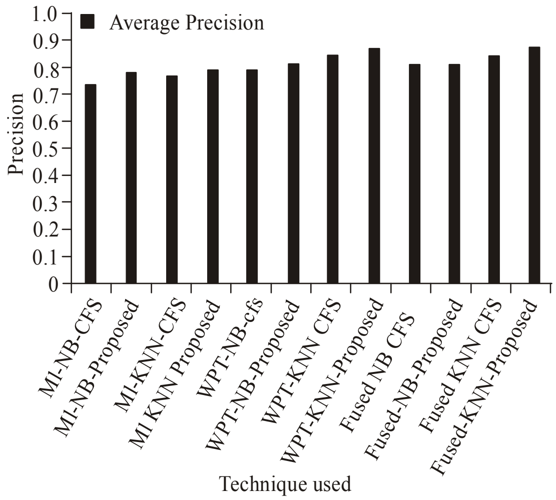

Fig. 3: Average precision

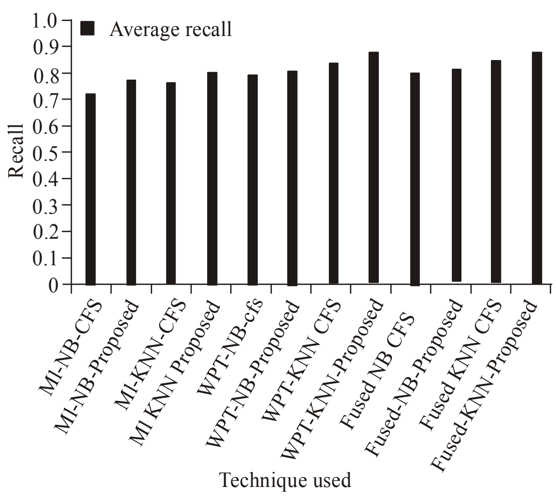

Fig. 4: Average recall

From Fig. 2 it is shown that the proposed feature selection with KNN classifier method achieves lower

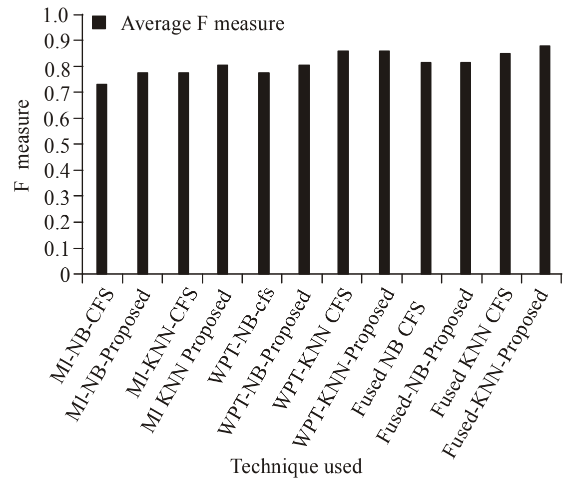

Fig. 5: Average F-measure

Root Mean Square Error (RMSE) than the other methods. It is observed that the error in classifier due to proposed feature selection method reduces by 0.8 to 6.82%.

From Fig. 3 it is observed that the proposed feature selection helps achieve higher average precision than the other methods.

Figure 4 shows that the proposed method improves the average recall of the classifier.

From Fig. 5 it is seen that the KNN classifier with fused vectors and proposed CFS based feature selection method achieves higher average F-measure than the other methods. It is observed that with the proposed feature selection, the fused feature vector performs better than 9.07% when compared to MI and by 0.68% for WPT features.

CONCLUSION

In this study, the MRI images from NBIA Dataset are classified as brain, chest and colon. Features are extracted using Moment Invariants and Wavelet packet tree in proposed framework, with extracted features set being reduced using CFS and Proposed CFS with cuckoo search algorithm. Naïve Bayes and KNN classify features. Results showed that the KNN classifier classifying the fused vectors with proposed feature selection method achieves 6.85% better classification accuracy than the Naïve Bayes. It is also seen that the proposed cuckoo based feature selection improves the classifiers accuracy by 2.1 to 6.98%. It is observed that with the proposed feature selection and the fused feature vector performs better than MI and WPT features and also significantly improves the performance of the classifiers.

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