International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, pp. 67-85, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

A CAD System for Automatic Classification Of Brain Strokes in CT Images

Ali Shalikar*, Mohammad Reza Ashouri and Mohammad Hossein Nadimi Shahraki

Faculty of Computer Engineering, Najafabad Branch, Islamic Azad University, Isfahan, Iran
*Corresponding Author's E-mail: *ali.shalikar@gmail.com*

Abstract

Brain stroke is one of the most important brain damages that if don't diagnose in first hours after happening, may lead to death of patient. There are different modalities for brain imaging but Computed Tomography(CT) is the most common, due to its less cost, less imaging time, more availability, stroke early detection and etc. According to current advances in technology of CT scanners, many images are produced per each patient and hence the radiologist detection error rate has been raised. In these conditions, Computer-Aided Diagnosis (CAD) systems can help radiologists to diagnose brain strokes rapidly and precisely. In this paper, we present a CAD system to classify brain CT images into hemorrhagic, ischemic and normal. The proposed CAD system applies Wavelet Packet Transform (WPT) to decompose input image into sub-images and then extracts texture features from sub-images using GLCM. The proposed method is evaluated on a dataset of 90 brain CT images and resulted in classification accuracy of 90%.

Keywords: Brain stroke, Discrete Wavelet Transform, Texture feature extraction, Wavelet Packet Transform.

1. Introduction

Stroke is a disease which affects vessels that supply blood to the brain. A stroke occurs due to two main reasons: rupture of blood vessel and blockage of blood vessel. In first condition, vessel bursts, often, due to high blood pressure and causes to bleed into brain matter. This type of stroke is called the hemorrhagic stroke. In second condition, the

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blood vessel is blocked, often, by blood clot and causes ischemia due to lack of oxygen, food, etc. This type of stroke is called the ischemic stroke. Accordingly, brain strokes can be classified into two major categories: hemorrhagic stroke (i.e., due to rupture of blood vessel) and ischemic stroke (i.e., due to blockage of blood vessel). There are different modalities for brain imaging such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Ultrasound, etc. Among these modalities, CT is the most common, due to its less cost, less imaging time, more availability, stroke early detection and etc. In CT images, a hemorrhage appears as a bright region (hyper dense), well contrasted against its surrounds whereas an ischemic stroke appears as a dark region (hypo dense), with the contrast relative to its surround depending on the time elapsed since the stroke occurred [1]. Three samples of brain CT images are shown in fig. 1.

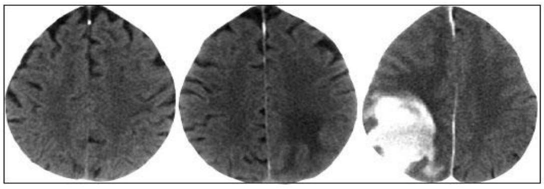

Figure 1: (from left to right) Normal, ischemic stroke and hemorrhagic stroke

Hemorrhagic stroke and ischemic stroke need to be treated differently (e.g., *fibrinolytic* is an essential drug to treat ischemic stroke whereas it can be fatal if prescribe for hemorrhagic stroke). Additionally, based on clinical researches, it has been proved that if the proper medication is not given within first three hours after happening of brain stroke, it may lead to death or great disability of patient [1]. Regarding text above, correct classification of brain strokes is so crucial. On the other hand, according to current advances in technology of CT scanners, too many images are produced per each patient. This condition increases radiologist error rate and also causes that diagnosis process by radiologist takes long time. Accordingly, these limitations make use of Computer-Aided

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Diagnosis Systems (CADs) inevitable. CADs are generally developed just to help human experts rather than to replace them. They usually aim at this goal by increasing classification accuracy and decreasing diagnosis time. Based on literature study, however they reduced diagnosis time extremely but they didn't improve classification accuracy obviously and need to be more reliable for real applications. Since CADs generally consist of two main steps; feature extraction and classification, they usually attempt to enhance classification accuracy with combining different feature extraction methods and classifiers. Feature extraction methods, in image applications, have generally relied on three common features: pixel intensity, color and texture. It has been proved that texture is the most efficient feature for medical image classification, particularly for brain images due to the complex nature of brain.

Our proposed CAD system uses combination of wavelet-based texture feature extraction method and SVM classifier for classifying brain CT images. It consists of four main steps. In the first step, input image is decomposed by wavelet transform (i.e., discrete wavelet transform and wavelet packet transform, alternatively) into its sub-images. In the second step, texture features are extracted using GLCM method. Extracted features are reduced by genetic algorithm in the third step. Finally, the selected features are classified using SVM classifier. The rest of the paper is organized as follows: section 2 reviews related works. The proposed method is explained in section 3. Section 4 evaluates the proposed method experimentally. Then, in section 5, our contribution and conclusions are discussed. Finally, some future improvements are given in section 6.

2. Related Works

Designing of a CAD system for automatic detection or classification of brain strokes drew attention of many researches. As explained in previous section, researchers have examined different combinations of feature extraction methods and classifiers to get higher classification accuracy. The approach in [2] exploits the fact that the hemorrhagic tissues are brighter than the normal tissues and hence uses a histogram-based k-means

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initial clustering followed by final segmentation using 3D morphological binary dilation of the initial clusters. An automatic method for brain stroke detection using wavelet analysis and classification was introduced in [1]. A rule-based approach for segmenting stroke lesion using seeded region growing was proposed in [3]. Computer aided detection of stroke by calculating Cohesive Rate (CR) of a series of CT images was proposed in [4]. A novel method was devised using Circular Adaptive Region of Interest (CAROI) in [5]. Knowledge based approaches were proposed in [6] and [7]. More recently, wavelet-based texture analysis has been used to first eradicate all the nasal cavity slices followed by intensity based thresholding [8] to identify the stroke-affected regions.

By reviewing previous works, we can categorize these works in three sub-domains:

- Most researches have considered the detection issue. Actually, there is a few of literature that considered the classification issue and hence it can be a strong motivation for us to do;
- Most researches have been done relying on detection of symmetry line of brain. These works assume that brain is symmetrical and compare two hemispheres of brain together (i.e., Equality of two hemispheres indicates non-existence of stroke). Since the brain can be asymmetrical and also same kind of brain stroke can occur in similar places of both hemispheres, the assumption would be failed in real applications;
- Previous works were usually based on pixel intensity. Since traditional pixel-based methods presented low performance due to partial volume effects (PVE) artifact, recent works have relied on texture features. However results show better performance rather than pixel-based methods but it needs to be enhanced.

3. Methodology

The framework of the proposed CAD system is illustrated in fig. 2.

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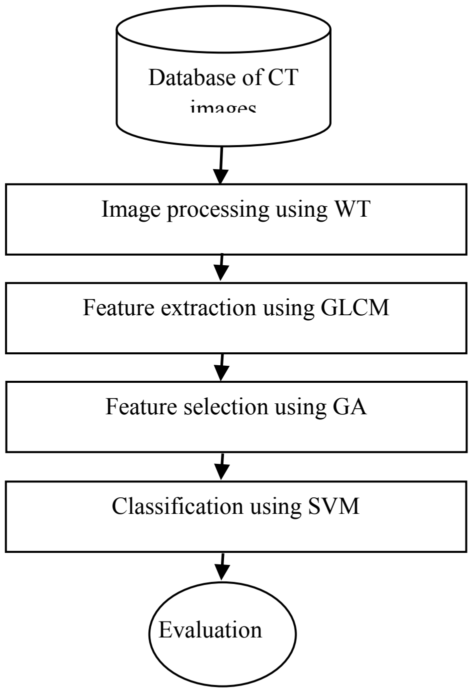

Figure 2: Block diagram of proposed CAD system

As can be seen in fig. 2, the CAD system consists of four main steps as below:

1. Applying of wavelet transform on input image and decomposing of image into sub-images.
2. Calculating of GLCM matrix for each sub-image and feature extraction.
3. Feature selection using genetic algorithm.
4. Classification using SVM and evaluation.

All of these steps will be explained in following sections:

3.1. Image Processing

Wavelet Image Processing enables computers to store an image in many scales of resolutions and thus reduces input data (i.e., input image), extremely. The advantage of image decomposition is that it enables the data to isolate and manipulate with specific properties [9]. In fact, wavelets are functions generated from one single function W by

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dilations and translations. The basic idea of the wavelet transform is representing any arbitrary function as a superposition of wavelets. Any such superposition decomposes the given function into different scale levels where each level is further decomposed with a resolution adapted to that level [10] and [11]. Wavelet transform has been used in image processing field due to its significant capabilities in signal processing. Additionally, it has been shown that wavelet-based methods continue to be powerful mathematical tools and offer computational advantage over other methods for texture classification. Discrete Wavelet Transform (DWT) is an extension of wavelet transform that has been commonly used in image processing. DWT suffers from major drawbacks such as lack of shift invariance and poor directional selectivity. These drawbacks caused to develop new extensions of wavelet transform such as Wavelet Packet Transform (WPT). The proposed method uses DWT and WPT, alternatively, in image processing step.

3.1.1. Discrete Wavelet Transform: The discrete wavelet transform is identical to a hierarchical sub-band system where the sub-bands are logarithmically spaced in frequency and represent an octave-band decomposition. By applying DWT, the image is actually divided (i.e., decomposed) into four sub-bands and critically sub-sampled, as shown in fig. 3(a).

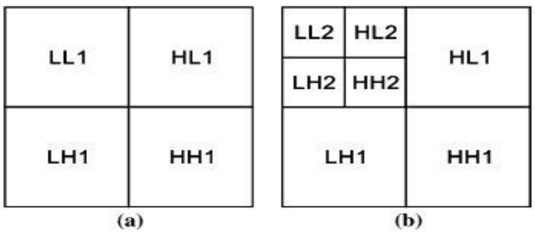

Figure 3: Image decomposition: (a) one level, (b) two levels.

These four sub-bands arise from separate applications of vertical and horizontal filters. The sub-bands labeled LH1, HL1 and HH1 represent the finest scale wavelet coefficients (i.e., detail sub-images) while the sub-band LL1 corresponds to coarse level coefficients

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(i.e., approximation sub-image). The sub-band LL1 is further decomposed to produce the next decomposition level. This results in two levels of wavelet decomposition as shown in fig. 3(b). Similarly, in order to obtain further decomposition level, LL2 will be used. This process continues until some final scale is reached. Fig. 4 shows typical discrete wavelet decomposition tree.

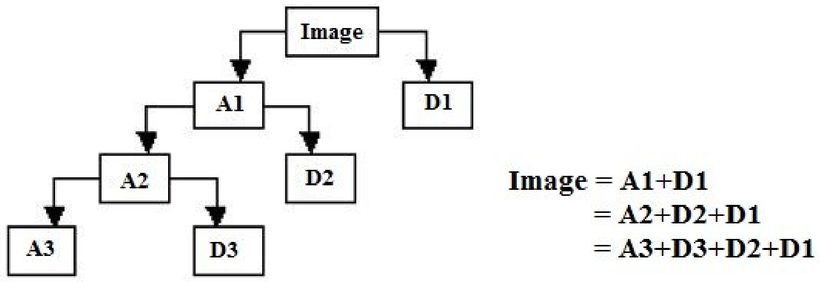

Figure 4: Wavelet decomposition tree

Since textures, either micro or macro, have non-uniform gray level variations, they are statistically characterized by the values in the DWT transformed sub-images (i.e., the features derived from the sub-images or their combinations). In other words, the features derived from the approximation and detail sub-images uniquely characterize a texture [10]. In order to apply the wavelet transform, two major parameters should be determined: wavelet family (i.e., mother wavelet) and the numbers of decomposition level. The most known family of orthogonal wavelets is Daubechies. Daubechies' wavelets are useful for texture classification and more popular due to their relations to multi-resolution analysis (MRA).

Based on the literature study, daubechies wavelet is considered as the best choice among the other wavelets for image applications [12]. Additionally, in order to determine the best order of daubechies wavelet, different orders are compared together and db4 is selected. Accordingly, the proposed method uses daubechies wavelet of order 4 as mother wavelet. Consistently, in order to achieve the desired decomposition level, an examination is done and classification accuracies of different decomposition levels are

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compared together. This examination is resulted in level 2 as the best decomposition level. Table 1 shows the results of six levels.

Table 1: Selection of optimal decomposition level

	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
CA	85.3	86.9	86.2	85.3	83.8	80.4

3.1.2. Wavelet Packet Transform: Since in the ordinary discrete wavelet transform only the approximation sub-band is split to produce further decomposition level, some information may be ignored. Wavelet Packet Transform (WPT) is a generalization of the DWT that was introduced by Coifman et al. [13] to improve the poor frequency localization of wavelet bases at high frequencies and thereby provide a more efficient decomposition of signals containing both transient and stationary components. In WPT, the details as well as the approximations would be split and hence it produces a full binary tree as shown in fig. 5.

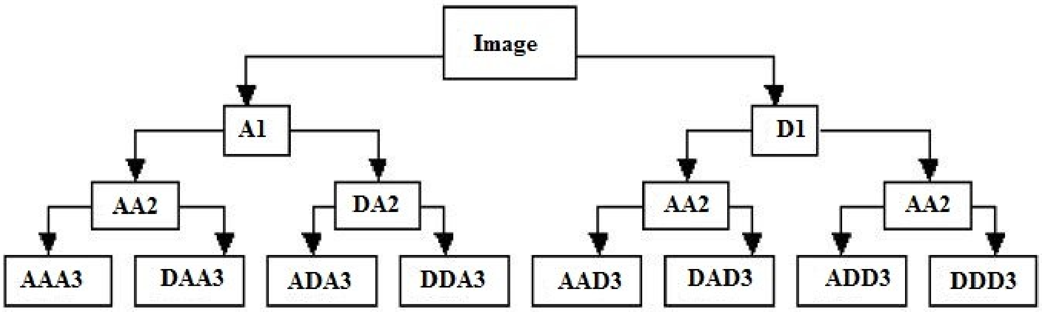

Figure 5: Wavelet Packet Decomposition Tree

Since in WPT, both detail sub-bands and approximation sub-bands take part in decomposition process, extracted features can be more efficient rather than discrete wavelet transform in classification tasks. In the proposed method, similar to DWT, db4 is used for WPT. Same examination as DWT is also done to determine optimal

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decomposition level and level 3 is chosen. Consequently, eight sub-bands are obtained in the proposed method using wavelet packet transform per each CT image.

3.2. Feature Extraction

The purpose of feature extraction is to reduce the original data set by measuring certain properties, or features, that distinguish one input pattern from another. It is a challenging task to extract good feature set for classification. There are different feature extraction methods but regarding section 1, texture-based ones can be most efficient for classifying the medical images. There are several texture-based feature extraction methods but Gray Level Co-occurrence Matrix (GLCM) is very common and successful. Despite high capability of GLCM for feature extraction, it is so time consuming. In order to overcome this drawback, in the proposed method wavelet transform (i.e., DWT and WPT, alternatively) is firstly used to decompose input image into four sub-images and then GLCM method is applied on each sub-image.

3.2.1. Gray Level Co-occurrence Matrix: Distribution of pixel gray levels can be described by second-order statistics like the probability of two pixels having particular gray levels at particular spatial relationships. This information can be summarized in two dimensional matrices called gray level co-occurrence matrices. GLCM is a square matrix of size equal to the number of grey levels in the image. The GLCM element $C(i, j, d, \theta)$ represents probability of the pair of pixels, which are located with an inter sample distance d and a direction θ, have a gray level i and a gray level j. Parameter d can be valued as 1 to maximum size of image and θ can be valued as four common angles: 0˚, 45˚, 90˚, 135˚ [14]. Consequently, four matrices would be obtained per each distance. In practice, the GLCM matrix is usually normalized to form probability matrix by dividing each element by the sum of all elements. Additionally, in order to avoid directional effects, average matrix of four directional matrices is usually calculated [15]. Since it has been proved that the GLCM matrix for d=1 contains more effective texture features rather

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than larger distances [16], in the proposed method *d* is set to 1. Accordingly, in the proposed method one matrix is obtained per each sub-image. After calculating of GLCM matrix, haralick method [17] is used to extract texture features. However haralick proposed fourteen features but Maximal Correlation Coefficient has not usually been used by subsequent papers due to its computational instability. Consequently, in the proposed method 52 (4×13) and 104 (8×13) features are obtained for DWT and WPT, respectively.

3.3. Feature Selection

In classification tasks, using of excessive features leads to what is called "curse of dimensionality" that degrades the performance of the classifier and increases the complexity. Consequently, in order to increase the classification accuracy and reduce the computation time, irrelevant, redundant and noisy features should be removed [18]. This procedure is called feature selection. There are different feature selection techniques but in this paper Genetic Algorithm is used.

3.3.1. Genetic Algorithm (GA): Genetic algorithm is one of the most useful feature selection techniques which has been very successful in many optimization areas. In classification tasks, it searches the optimal feature subset that minimizes the dimensionality of input space and maximizes the classification accuracy. Each feature subset is encoded into a vector called chromosome and each chromosome consists of genes which are equal to features. In binary form of chromosome a 1 in bit position indicates that corresponding feature should be selected and 0 indicates that feature should not be selected. Chromosomes are combined via a crossover operator to produce offspring and finally next generation. A mutation operator is generally applied to each chromosome to reduce the probability of local convergence. The chromosomes of new generation are then evaluated via a fitness function in (1) where W_A is the weight of accuracy and W_{nb} is the weight of N features participated in classification where $N \neq 0$.

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$$\text{fitness} = W_A \cdot \text{Accuracy} + W_{nb}/N \tag{1}$$

A fitness value will be used to measure the fitness of a chromosome and decides whether a chromosome is good or not. GA starts by randomly creating an initial population of chromosomes. GA uses then three operators to produce next generation from the current generation: *reproduction*, *crossover* and *mutation.* It eliminates the chromosomes of low fitness and keeps the ones of high fitness. Thus more chromosomes of high fitness move to the next generation. This process is repeated until a good chromosome (i.e., solution) is found.

In the proposed method, an initial population of 100 chromosomes is randomly created and then ranked-based roulette wheel selection method is used to select the fittest chromosomes to generate next generation. The genetic operators, single point crossover and mutation are used. The crossover rate is 1 and mutation rate is 0.1. Iteration number of 100 is used as stopping criterion of algorithm. Finally, four features are selected as the best features: Energy, Entropy, Variance and Inverse Difference Moment (IDM). These features are extracted from both detail and approximation sub-bands and hence 16 and 32 features are obtained for DWT and WPT, respectively. These features are used as the input vector of SVM classifier for classifying the images into three classes: hemorrhagic stroke, ischemic stroke and normal.

3.4. Classification

Classification is a crucial part of a CAD system therein classifier assigns one unknown sample to a predefined class based on previous knowledge. Support Vector Machine (SVM) is used as classifier in the proposed method. SVM is a powerful supervised classifier and accurate learning technique that has been introduced in 1995. It is derived from the statistical theory developed by Vapnik in 1982 [19]. It yields successful classification results in various application domains (e.g., medical diagnosis) [20]. SVMs [21] perform pattern classification by determining the separating hyperplane with

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maximum distance to the closest points in the training set. These points are called support vectors. This process is illustrated in fig. 6.

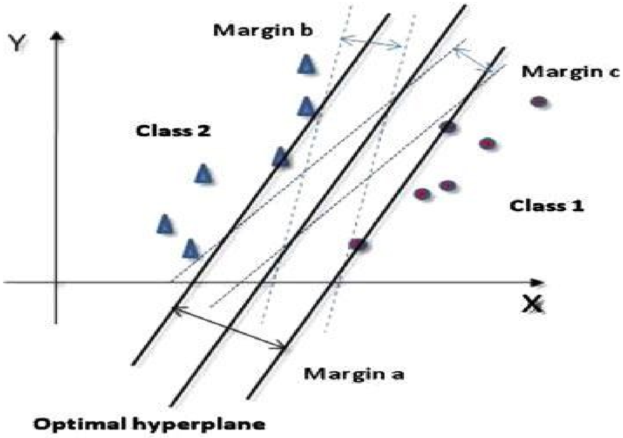

Figure 6: Selection of the optimal hyperplane in SVM

As can be seen in fig. 6, class1 and class2 can be separated by three hyperplanes but hyperplane *a* is optimal because margin *a* creates the biggest distance between two classes.

The decision function of SVM is displayed in (2):

$$f(x) = sign\left[\sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b\right] \tag{2}$$

Where x is the data point to be classified, x_i *is* support vector, N is the number of support vectors, b is a constant decided from training and $y_i \in \{-1, 1\}$ is the class label of the support vector x_i . The coefficients α_i are the solutions of a quadratic programming problem. The margin, which is the distance of the support vectors to the hyperplane, is thus given by (3):

$$M = \frac{1}{\sqrt{\sum_i^N \alpha_i}} \tag{3}$$

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The margin is an indicator of the separability of the data using corresponding hyperplane (fig. 6). Since the real-world problems are often not linearly separable, SVMs use kernel functions to consider such conditions. By applying a kernel function K, the input data vectors are mapped into a higher-dimensional space. In this space, the mapped data vectors could be linearly separable or have improved separability [22]. Table 2 shows four popular kernel functions. The Radial Basis Function (RBF) kernel is commonly considered as the most powerful but linear kernels are best understood and are the simplest to apply [22]. By doing some parameter configuration, a RBF kernel can be converted to a linear one [23]. The linear kernel is suitable for solving linear separable problems. If target classes are not linear separable, they have to be projected to a higher dimension space where they are linear separable or easier to be separated. This process is done using non-linear kernels, such as the RBF kernel. In the proposed method, all kernel functions displayed in table 2 are evaluated and linear is chosen as the best.

Table 2: The most popular kernel types

Kernel Type	Kernel
Linear	$x_i^T x$
Polynomial	$(x_i^T x + \tau)^d$
Radial Basis Function	$\exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right)$
Sigmoid	$\tan h\,(kx_i^T x + \theta)$

Inherently, SVMs are binary classifiers but using decision fusion they can be used as multi-class classifiers. Numerous SVM-based multi-class methods are utilized to the same data sets and use the same partitioning, such as One-Against-One (OAO) [21] and One-Against-All (OAA) [24]. The OAA model constructs n SVMs for n-class classification. The ith SVM is trained with all the samples from the ith class with positive labels against all samples from the rest of classes with negative labels. Another method,

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OAO, is partitioned by the pair-wise classes using training binary SVMs. The OAO model consists of n $(n-1)2$ binary SVMs for multi-class classification.

Each of the n $(n-1)2$ SVMs needs decision strategies to determine the predicted result, such as the Error-Correcting Output Code (ECOC) [22], Directed Acyclic Graph (DAG) [24], Majority-Voting (MV) and so on. DAG would broadcast errors if wrong predictions occur [25]; ECOC increases the computations if the correction is a large number [26]. MV combines numerous opinions of classifiers to obtain a decision. Numerous multi-class SVM studies are focused on a small sample size, and OAO and MV are commonly used methods for classification and decision that are also used in the proposed method.

4. Experimental Results

The experimental results of the proposed method are explained in this section. The proposed method is implemented using MATLAB (7.11). In order to implement the proposed method, a dataset of 90 real human brain CT images is used. The dataset consists of 30 hemorrhagic strokes, 30 ischemic strokes and 30 normal images. The images are totally axial, of 256×256 size in format of JPEG and collected from Babol Clinic located in Babol, Mazandaran, Iran.

K-fold cross validation method is used to evaluate the proposed method. In k-fold cross validation method the data is divided into k parts and classification process is repeated k times. In each iteration, one part is used as the test data and the rest is used as the training data. In this paper, k is set to 10. Results are shown in a table called Confusion Matrix (i.e., Contingency Table). Table 3 shows typical confusion matrix.

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Table 3: Confusion matrix of three-class classification task

		predicted class		
		Class H	**Class I**	**Class N**
Real class	**Class H**	T_H	e_{HI}	e_{HN}
	Class I	e_{IH}	T_I	e_{IN}
	Class N	e_{NH}	e_{NI}	T_N

Several measurements can be extracted from confusion matrix such as Sensitivity, Specificity and Classification Accuracy and etc. In this paper, CA is used to evaluate the proposed method. CA is also correct classification rate of classifier and shows proportion of true prediction numbers of classifier in total predictions. Equation (4) shows formula of CA according to table 3:

$$CA = \frac{T_H + T_I + T_N}{T_H + T_I + T_N + e_{HI} + e_{HN} + e_{IH} + e_{IN} + e_{NH} + e_{NI}} \quad \textbf{(4)}$$

In evaluation step, CA is obtained 90%, 86% and 70% respectively for the proposed method using WPT, the proposed method using DWT and the method without wavelet transform (GLCM). This comparison is illustrated in fig. 7.

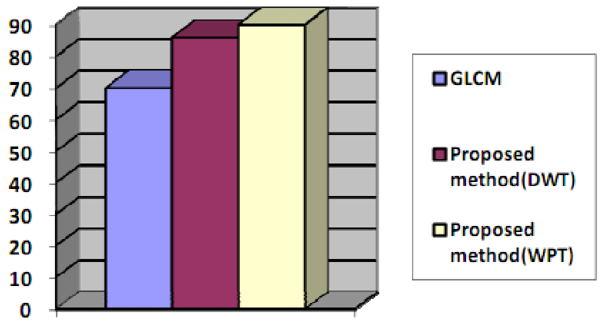

Figure 7: Classification accuracy of three discussed methods

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Fig. 7 shows influence of wavelet transform in feature extraction. Actually, better classification accuracy is achieved for GLCM by adding one step wavelet transform before. Additionally, the proposed method using WPT is resulted in higher classification accuracy rather than DWT. Computational times of the three discussed methods are calculated and show that however there is no obvious different between the times of DWT and WPT but WT can decrease computational time intensively.

Conclusion

In this paper, a new method was proposed for detection and classification of brain strokes in CT images. Actually, the images were classified into three classes: hemorrhagic stroke, ischemic stroke and normal. The proposed method was represented as a CAD system with four main steps. In the first step, the input image was decomposed using DWT and WPT separately. In the second step, GLCM matrices were firstly calculated for each sub-image obtained from the first step and then thirteen haralick texture features were extracted from each average GLCM matrix. The CAD system in the third step was included a GA-based feature selection technique and feature vectors with length of 16 and 32 were resulted in this step. Finally, SVM was used to classify selected texture features. In order to evaluate the proposed method, 10-fold cross validation method was used. This paper found out the influence of wavelet transform to increase classification accuracy and decrease computational time. Moreover, this paper proved superiority of WPT over DWT for classifying the human brain CT images.

Future Works

Future works could deal with classification of other brain abnormalities such as tumors. Since the CAD system consists of several steps, different combinations of techniques can be evaluated to enhance classification performance. For instance, other extensions of WT such as Dual-Tree Complex Wavelet Transform can be used for image decomposition. Additionally, other selection techniques can be used instead of GA.

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Alternatively, neural network techniques can be used as classifier in the proposed method.

Acknowledgements:

We would like to thank S. Borzouyi and H. Amiri for their invaluable efforts in providing images.

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