Computer Based Method to Automatically Identify the Regions of Intracerebral Haemorrhage on Diffusion Weighted Magnetic Resonance Images

Supriya S. Shanbhag, G. R. Udupi, and K. Ranganath

Abstract—In recent times several methods for automated diagnostic systems have been proposed to overcome the problems faced due to large number of patients, and the necessity of having high accuracy when dealing with a human life. Traditional way of examining the Diffusion Weighted (DW) brain images of the human subjects with Intracerebral Haemorrhage (ICH) involves the inspection of specific features, by a human observer. Present work makes an effort to develop a computer based method to automatically identify the regions of ICH on DW brain images of the ICH subjects, and thereby help in transforming the conventional qualitative investigative criteria into a quantitative feature classification problem. In this direction feature extraction techniques, namely Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) are employed to provide description of the significant properties of the DW brain images. Subsequently, K-Nearest Neighbor (KNN) method of image classification is employed to analyze the properties of the extracted features. The maximum classification efficiency of the KNN classifier for the correct output classification of the ICH subjects using DCT method is obtained as 71.50% for k value = 1.00, and using DWT method is obtained as 90.00% for k value = 9.00, respectively. Results imply that the technique proposed in the present work could positively be helpful in the fast diagnosis of the ICH subjects, even in the absence of a medical expert.

Index Terms—Automatic Identification; Discrete Cosine Transform; Discrete Wavelet Transform; Diffusion Weighted Images; Intracerebral Haemorrhage; K-Nearest Neighbor; Magnetic Resonance Images.

I. INTRODUCTION

Neurological disorders cause a huge challenge to healthcare, primarily in developing countries, due to insufficient resources and manpower that are not capable to deal with the rising burden [1]. Stroke is the most frequent neurological disorder, in terms of morbidity and mortality, and occurs when the blood circulation to the brain fails, resulting in momentary or permanent failure of working brain tissue [2]. Intracerebral Haemorrhage (ICH), a type of haemorrhagic stroke, accounts for up to 15% of all strokes and has a 40% risk of death [3]. In spite of its rather high occurrence and poor associated outcomes, there has been limited success in establishing effective therapies for ICH, fundamentally due to insufficient quantity and quality of clinical studies [4]. While conventional Magnetic Resonance Imaging (MRI) has been commonly used to assess the appearance and underlying biophysical basis of developing ICH, research studies [5], [6]-[10] have identified Diffusion Weighted-Magnetic Resonance Imaging (DW-MRI) as a valuable investigative resource in identifying and in localizing ICH [11]-[13]. There have been reports which indicate that there is restriction to diffusion within the area of ICH, prior to and following cell lysis, producing bright signal intensity on Diffusion Weighted (DW) images of the brain [14], [15]. Further, with the progression of haemorrhage the signal intensity variations change from being hyper-intense to hypo-intense [14]-[16]. DW-MRI technique thereby facilitates the visualization of the changes in the rates of water diffusion by resulting in a bright imaging appearance in the areas of ICH, as compared to the normal areas, at different ICH stages. Traditional means of examining and analyzing ICH subjects depends on noticing the presence of specific features, by a human observer. However, in recent times numerous methods for automated diagnostic systems have been proposed to overcome the problems faced due to large number of patients, and the need for constant observation of certain medical conditions. Studies have been carried out in the past that investigate into the signal intensity characteristics of ICH on DW brain images, and further quantify these signal intensity variations to derive useful information about the state of brain tissue in the ICH subject [17], [18]. However, identification of the regions of signal intensity variations that characterize the occurrence of ICH on DW brain images has been done manually by visual inspection. Towards this end the present work makes an effort to develop a computer based method to automatically identify the regions of ICH (regions of signal intensity variations) on DW brain images of the ICH subjects, without any human intervention. The proposed method along with the work carried out earlier [17], [18] would provide a complete automated system that would identify the ICH regions on DW brain images and also classify the ICH subjects into different stages of haemorrhage. Thereby the adoption of the present work in the medical diagnosis of ICH subjects would ease the estimation process and help in providing important details for the further management and medicinal decisions, even in the absence of a medical expert.

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II. MATERIAL AND METHODS

A. Data Acquisition of DW Brain Images

The clinical data acquired in the present work involves the use of clinical MRI with 1.5 Tesla symphony maestro class MR scanning system from Siemens. DW-MRI is performed by using a multisection, single-shot, spin-echo, echo-planar pulse sequence with following parameters: Repetition Time [TR]=3200 ms, Echo Time [TE]=94 ms, acquisition matrix=128 x 128, Field of View [FOV]=230 mm x 230 mm, and diffusion gradient value of b=1000 s/m² along 19 axial slices, 5 mm thick slice, and intersection gap of 1.5 mm. Among all the consecutive subjects admitted, only those subjects who showed isolated ICH without the presence of underlying tumor or infarction, on initial radiologic and follow-up examinations were selected. For all the subjects with ICH considered, the appearance of haemorrhage was confirmed by ruling out the possibility of bright intensity due to T2 shine through effects. This was done by verifying the appearance of hyperintensities on DW images and concomitant-reduced ADCs relative to the contralateral normal brain in their initial MRI studies. The ethics approval was obtained from the committee of clinical research at the RAGAVS diagnostic and Research center, Bangalore, India, and Vikram Hospital, Bangalore, India. The axial DW brain images obtained from the MR scanning system in the DICOM format are converted to bit map (BMP) format for further processing. This step is carried out in order to minimize the difficulty in implementing algorithms for image manipulation and attain better speed in processing the images.

B. Identification of the Regions of ICH Using Machine Learning

The regions of ICH on DW images of the human brain present restricted diffusion resulting in non-uniform spatial intensity distribution in the affected areas. In contrast, the healthy areas of the brain display a uniform spatial intensity distribution. The first step in identifying the regions of ICH on DW brain images is the process of feature extraction that provides the description of the significant properties (signal intensity characteristics) of the image into a feature space. Subsequently, an image classification system is employed to analyze the properties of the extracted features using a suitable classifier. In the present work Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) techniques have been adopted to extract the distinctive features of the ICH regions on the DW brain images. Further, an attempt is made to implement the image classification system using K-Nearest Neighbor (KNN) method, based on the feature set extracted using the DCT and DWT techniques.

C. DCT Based Feature Extraction of DW Brain Images

The proposed feature extraction method is based on using the two dimensional (2-D) DCT to obtain typical features from the DW brain images. The approach involves taking the transformation of the input image as a whole and separating the relevant coefficients. Thereby, 2-D DCT is first applied on the entire input image resulting in low and high frequency coefficients feature matrix of same dimension. Next, selected DCT coefficients are used as a feature vector from the input image to construct feature space. The 2-D DCT decomposes an image into its basic three frequency components, namely, low, middle and high, each containing some information in the image. Mathematically, the 2-D DCT of an M x N image is given by (1) [19].

\[
F(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \cos \left( \frac{\pi u x}{M} \right) \cos \left( \frac{\pi v y}{N} \right)
\]

where \(f(x,y)\) is the intensity of the pixel at coordinates \((x,y)\), \(u\) varies from 0 to \(M - 1\), and \(v\) varies from 0 to \(N - 1\), where \(M \times N\) is the size of the image.

The 2-D DCT applied to an \(M \times N\) image results in compressing all the information of the image and concentrating it in a small number of coefficients situated in the upper-left corner of the resulting real-valued \(M \times N\) DCT matrix. The pixel values of the transform image are either zero or some low values, with the exception of the values located at the top left corner, where the intensities are very high. Most of the significant features of the original image are attributed to these low-frequency, high intensity coefficients in the DCT matrix [20]. Proposed method employs selecting features from the first-row-column-diagonal of the DCT matrix as shown in Fig. 1.

![Image 379x308 to 475x405](image)

Fig. 1. First-row-column-diagonal method of features selection from the DCT matrix.

Feature vector is generated by calculating the mean and standard deviation of the first-row-column-diagonal values in the DCT matrix [21] resulting in six attributes of the input image. The mean and standard deviation values are evaluated using (2) and (3), respectively. The DC component is not included in the evaluation of the features set since it represents the average intensity of the image. As a result, the 2-D DCT method results in a feature set comprising of six characteristic features of the input image that are further functional in the image classification system.

\[
\text{Mean}(x) = \frac{1}{n} \sum_{i=1}^{n} x_i
\]

(2)

\[
\text{Standard deviation}(x) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \overline{x})^2}
\]

(3)

where \(x\) is the data vector.
D. Feature Extraction of DW Brain Images Using Wavelet

According to wavelet theory, a conventional 2-D DWT can be treated as similar to filtering the input image with a bank of filters, wherein, the output of each level consists of four sub-images with 2:1 down sampling. The input image is passed through high-pass and low-pass filters resulting in a detailed coefficient subset and an approximation coefficient subset at the first level. The coefficients of the high-pass and low-pass filters rely on the type of wavelet function. The single-level 2-D wavelet decomposition yields the approximation coefficients matrix \( cA \) and details coefficients matrices \( cH, cV, \) and \( cD \) (horizontal, vertical, and diagonal, respectively), acquired by wavelet decomposition of the input matrix. To attain a multi-resolution analysis, repetitious transformation is performed. The decomposition process by 2-D DWT from the high scale to the low scale is shown in Fig. 2. The second level decomposition is expanded on \( cA1 \) component. This process is duplicated until the desired final level is yielded [22].

![Image analysis by using 2-D DWT](image1)

There are a range of wavelet transforms that can be applied, such as Haar, Coiflet, Meyer, Morlet and others, with each of them having their own unique features. Among them Haar transform is one of the simplest and basic transformations from the space domain to a local frequency domain [23]. In the present work the input DW brain image is decomposed into three levels by Haar wavelet, and the approximation coefficients and details coefficients at each decomposed levels are used to extract the features from the input image. Two attributes, namely, mean and standard deviation are evaluated from the approximate and detail DWT coefficients obtained from all the three levels of signal decomposition using (2) and (3), respectively. As a result, eight features are derived from the approximate and the detail DWT coefficients at each level of signal decomposition. Since the present work uses three levels of decomposition, the overall feature set comprises of twenty-four characteristic features of the DW brain image that are further applied in the image classification system.

E. Image Classifier System Using KNN

There are a variety of classifiers available that are individually found suitable to classify a particular kind of feature vectors depending upon their characteristics. In general, there are two phases of processing in the classification algorithms: training and testing. In the training phase, a typical property of the image features is identified and based on them a characteristic description of each training class is formed. In the testing phase, the image features are classified depending on these feature-space partitions. The KNN is one of the simplest machine learning algorithms for classification, based on closest training samples in the feature space. In a KNN [24], the top k closest instances are located and allowed to vote, in contrast to finding the only closest instance in the instance space. The value of k decides how many neighbors influence the classification. Further, with the increase in the value of k the classifier becomes locally less sensitive due to smoothing effect. The most appropriate value of k is largely dependent on the data, and in general higher values of k suppress noise, yet, makes the classification boundaries less distinct. Training period of KNN algorithm involves the storage of feature vectors and labels of the training images. Therefore, each training data is associated with a set of vectors and class label related with each vector [25]. In order to classify an object, a majority vote of its neighbors is considered, with the object being allocated to the class most common amongst its k nearest neighbors. The KNN algorithm finds the k nearest neighbors by measuring the distance between the unknown sample and the training data samples. In the present work the distances of the neighbors are calculated using Euclidean distance method, since this method is very simple and most commonly used to calculate the distance between any pairs. For an n-dimensional Euclidean space, the distance between two samples a and b is defined by (4).

\[
D = \sqrt{\sum_{i=1}^{n}(a_i - b_i)^2}
\]  

where \( a_i \) and \( b_i \) are the coordinates of a and b in dimension i.

The block diagram of the KNN classifier is shown in Fig. 3. The distances between the test feature vector (x) and the entire training data set (\( y_1 \) to \( y_n \)) are calculated. Further, the features decided by the value of k that have minimum distances are subjected to majority vote to result in a final decision [25]. The performance of the KNN classifier depends on choosing the optimal number of neighbors i.e. the k value. Generally, the value of k is chosen empirically, wherein, each possible value of k is tried and the value that results in the best performance is chosen to define the classifier. In the present work an attempt is made to find the optimum value of k by verifying how different values of the k parameter perform on the input data samples.

![Block diagram of the KNN classifier](image2)
the different possibilities of k values that could result in good performance of the classifier [26]. The holdout method is the simplest type of cross validation that uses a percentage of the training data set for validation. Normally, the training data samples are randomly divided into two groups: two third of the data samples used for training and one third used for validation. The training data set is used to train the classifier and the validation data set is used to approximate the error rate of the trained classifier. The training and the validation data sets are carefully chosen to have a good combination of all class labels and data points of the entire input data set. The procedure of adjusting the values of k is organized using the bisection method. The bisection method is one of the simplest root-finding algorithms that continually divides a search interval in half and then selects the subinterval in which a root exists [26]. Initially, the upper (k = number of samples in training data set) and lower (k = 1) bounds of the entire search interval are chosen. Further, only odd values of k are considered in the search interval in order to avoid two class labels achieving the same score. The error rate is calculated at different k values for each of the validation data using (5).

\[ \text{Error rate} = \frac{\text{number of errors}}{\text{number of holdout data}} = \frac{c}{d} \]  

(5)

where holdout data refers to the data not used in training, but used to assess the performance of the KNN classifier. The block diagram of the proposed technique to obtain the optimal k value is shown in Fig. 4. The k value that ensures minimum error rate is chosen as the optimal k value. Finally, the generalization performance of the KNN classifier is tested on the test set and the corresponding value of correct classification function is calculated.

The overall procedure applied to automatically identify the ICH regions on DW brain images is shown in Fig. 5. The input to the system is the DW brain MR image of a subject. The significant characteristics of the input image are extracted using the DCT and DWT feature extraction techniques and further applied to the KNN image classifier to classify the input DW brain image as either ICH or normal type. The variation in the signal intensity in each area on the axial DW brain image is examined by extracting the characteristic features of the sub-regions of that area and further applying them to the image classification system. The sub-regions that are classified as ICH collectively constitute the ROI for that particular area. The Fig. 7 shows the DW brain image of a subject with ICH in area 4, axial slice 7. For the same subject, Fig. 8 shows the ROI \[ I(x, y) \] and the corresponding sub-regions \[ f(x, y) \] on the ICH side.

III. IMAGE ANALYSIS

The DW brain image obtained from the MR scanning system is divided into six areas as shown in Fig. 6. Each area on the DW image is divided automatically into smaller sub-regions corresponding to an image size represented by \( (M \times N) \) pixels. Analysis is carried out with different sets of values for M and N, to avoid distortion of the image and to arrive at the proper sub-region size that includes the appropriate details of the signal intensity variations [27]. Subsequent to the analysis, the typical values for M and N are chosen in the range between 13 to 18 pixels.
IV. RESULTS AND DISCUSSIONS

In order to compare the different methods proposed (Fig. 5) for the automatic identification of the region of ICH on DW brain images, the classification efficiency metric (percentage of the total number of patterns in the testing data set that are correctly classified) is employed. Image classification is carried out by dividing the DW brain images into training data set and testing data set. The classifier is trained using the training data set and the accuracy and effectiveness of the trained network is determined using the testing data set. The features of all the DW brain images to be classified are extracted and compared with the features of the training models to identify the unknown image. In the KNN classifier the neighborhood parameter k plays an important role on the performance as it controls the size of the neighborhood and therefore the smoothness of the density estimates. The KNN classifier model is implemented by using MATLAB software and is designed and trained with adequate number of input-output patterns. The training data set comprised of 600 DW brain images, out of which 300 were from ICH subjects and 300 from normal subjects. For the purpose of testing a set of 200 DW brain images were employed.

A. KNN Classifier Using DCT Based Feature Extraction to Classify ICH regions

The six characteristic features obtained from the DW brain image (to be classified) by applying DCT feature extraction technique are passed to the KNN classifier to carry out the image classification, i.e. classifying the input image as either ICH or normal type. The plot shown in Fig. 9 presents the variation in the classification efficiency of the KNN classifier with varying values of k. It is observed that the maximum classification efficiency of the KNN classifier for the correct output classification for ICH subjects is obtained as 71.50% for k value = 1.00.

B. KNN Classifier Using DWT Based Feature Extraction to Classify ICH Regions

The twenty-four characteristic features obtained from the DW brain image (to be classified) by applying DWT feature extraction technique are passed to the KNN classifier to carry out the image classification, i.e. classifying the input image as either ICH or normal type. The plot as shown in Fig. 10 presents the variation in the classification efficiency of the KNN classifier with varying values of k. It is found that the maximum classification efficiency of the KNN classifier for the correct output classification of ICH subjects is obtained as 90.00% for k value = 9.00.

V. CONCLUSION

A computer based method to automatically identify the regions of haemorrhage on DW images of the human brain is developed using DCT and DWT feature extraction techniques, followed by KNN image classifier. The maximum classification efficiency of the KNN classifier for the correct output classification of ICH subjects using DCT method is obtained as 71.50% for k value = 1.00, and using DWT method is obtained as 90.00% for k value = 9.00. The high accuracy values obtained from the proposed method is an indication that it can be helpful to the radiologists as it could positively simplify and speed up the assessment process, by eliminating the need of human intervention. Consequently, implementation of the proposed method in the clinical diagnosis of ICH subjects could be useful.

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