Automatic Detection and Segmentation of Ischemic Stroke Lesion from Diffusion Weighted MRI using Contourlet Transform Technique

Shyna A
Department of computer Engineering
College of Engineering, Chengannur
Alappuzha, India

Deepa J
Associate Professor,Department of Electronics Engineering
College of Engineering, Chengannur
Alappuzha, India

***Abstract*—Diffusion Weighted Magnetic Resonance Imaging (DWI) considered as the most sensitive technique in detecting early ischemic stroke in the brain. This paper present a novelContourlet transform based approach for automatic detection and segmentation of ischemic stroke lesion from brain DWI.The proposed method is divided into two phases. In the first phase, features are extracted using co-occurrence matrix of the Contourlet coefficients of the input image. These extracted features are the input of the SVM classifier, which classifies the images between Normal and Abnormal. In the second phase, K-means clustering is used to segment Ischemic stroke lesion from abnormal image after enhancement using contourlet transform. The present work is applied on real data of 240 Diffusion weighted images. Matlab R2010b is used for implementation of the algorithm. Experimental results shows that the developed algorithm provides 100% classification accuracy with SVM RBF kernel function.**

Keywords—Diffusion Weighted Images,ContourletTransform, Support Vector Machine, K-means clustering.

I. IINTRODUCTION

Medical Image Processing has emerged as one of the most important tools to identify as well as diagnose various disorders. Imaging helps the Doctors to visualize and analyse the image for understanding of abnormalities in internal structures.Stroke or cerebrovascular accident is a medical condition caused due to inadequate supply of blood (lack of oxygen and nutrients) to the brain cells which damages them and may result in their death. It occurs when a blood vessel either bursts or there is a blockage of the blood vessel. Stroke caused due to a clot in the blood vessel is referred to as ischemic stroke and that due to a blood vessel rupture is referred to as hemorrhagic stroke. In an ischemic stroke, blood supply to part of the brain is decreased leading to death of the brain tissue in that region.As the average human life span has increased, stroke has become the third leading cause of death worldwide after heart disease and cancer. Between these, ischemic stroke accounts for about 80% of all strokes [1].

There are many brain imaging modalities used in stroke diagnosis [2]. ComputedTomography (CT) is extensively used for identification of suspected stroke in the initial stages. Early identification of ischemic changes in non-contrast CT is a challenge and depends on the reviewer experience. In the first 6 hours from the onset of the stroke, the CT scan fails to capture the early ischemic changes in most cases.Magnetic resonance imaging (MRI) is one of the popular, painless, non-radiation brain imaging technique. Conventional MRI is more sensitive to ischemic changes as compared to CT. A subtle change in the contrast is easier to identify on the MRI. However, such changes are not usually visible up to 3-4 hours from the onset of stroke [2,3]. Diffusion-weighted MRI (DWMRI or DWI) is an advanced technique which measures the strength of water diffusion within a tissue structurewhich have their own particular diffusion character. Image contrast is depends on thediffusivity, where lesion or tissues with high diffusion appear dark (hypointense), andlow diffusion appear bright (hyperintense)[4].DWI provides higher lesion contrast compared to conventional MRI. Research has shown that DWI is considered as the most sensitive technique in detecting early acute ischemic stroke.

Ischemic stroke lesions appear hyper intense on DWI and are inhomogeneous,with complex shapes and ambiguous boundaries with observed intensity variation which makes manual detection and segmentation of stroke lesion difficult and time consuming. Soa computer automated algorithm to evaluate DWI images have therefore great clinical usefulness. The basic concept of CAD (Computer Aided Diagnosis) is to provide a computer output as a second opiniont o assist radiologist's image interpretation by improving the accuracy and consistency of radiological diagnosis and also by reducing the image processing time[5]. To automate the stroke detection it has to use different image processing and pattern recognition methods such as classification, feature extraction, segmentation etc.

Several works are already done for detection of stroke in medical images.Tao Chan [6] proposed a method to develop a computer aided detection system that improves diagnostic accuracy of small acute intracranial hemorrhage (AIH) on brain CT. Milan Matein et al. [7] proposed a method for automatic segmentation and labeling of computed tomography (CT) head images of stroke lesions. The above two methods require Knowledge engineering and domain experts for building and maintaining the rules and the system.MR images are very complex to be efficiently described and handled using rules.N.HemaRajini,R.Bhavani [8] proposed a method for the automated detection of ischemic stroke using segmentation,mid line shift and image feature characteristics, which separate the ischemic stroke region from healthy tissues in computed tomography images.This method fails when same type of stroke occurs symmetrically on both sides of brain.MayankChawla et al [9] proposed an automated method to detect and classify an abnormality into acute infarct, chronic infarct and hemorrhage at the slice level ofnon-contrast CT images. This method does not consider the condition where the same type of stroke occurs symmetrically in both hemispheres.Bhavna Sharma, K.Venugopalan [10] proposed a method for Automatic Segmentation of Brain CT Scan Image to Identify Hemorrhages. The robustness of this method depends on the different artifacts usually present in CT images.N.MohdSaad [11] proposed a method for fully automatic segmentation of brain lesions from diffusion-weighted magnetic resonance imaging (DW-MRI or DWI) using Region growing method. MultiresolutionalContourlet analysis provides the sub images of an image localized in different spatial frequency[12]. Because these images have different characteristics, it is quite convenient to use them for distinguishing tissue types from each other and tissue analysis.Contourlet transform based detection and segmentation algorithm is used in the presented work.

This paper is organized as follows. Section II discussed the proposed methodology in detail. Experimental Results of classification and segmentation,Performance analysis of SVM classifier are described in Section III. In section IV, conclusions of this work are presented.

II. PROPOSED METHODOLGY

The present works consistof two phases,namely,Classificationand Segmentation.Classification phase is used to classify the input image into either Normal or Abnormal based on the abnormality.If the result of the classification phase is abnormal,Segmentation stage is performed to extract the ischemic stroke lesion from the abnormal image.The block diagram of the proposed method is shown in Fig 1. Every classifier has two Phases, Training Phase and Testing Phase. For classification, it is not practical to pass entire image details to the classifier. So it has to identify a set of relevant features that can be substituted instead of the entire dataset without losing its actual meaning.

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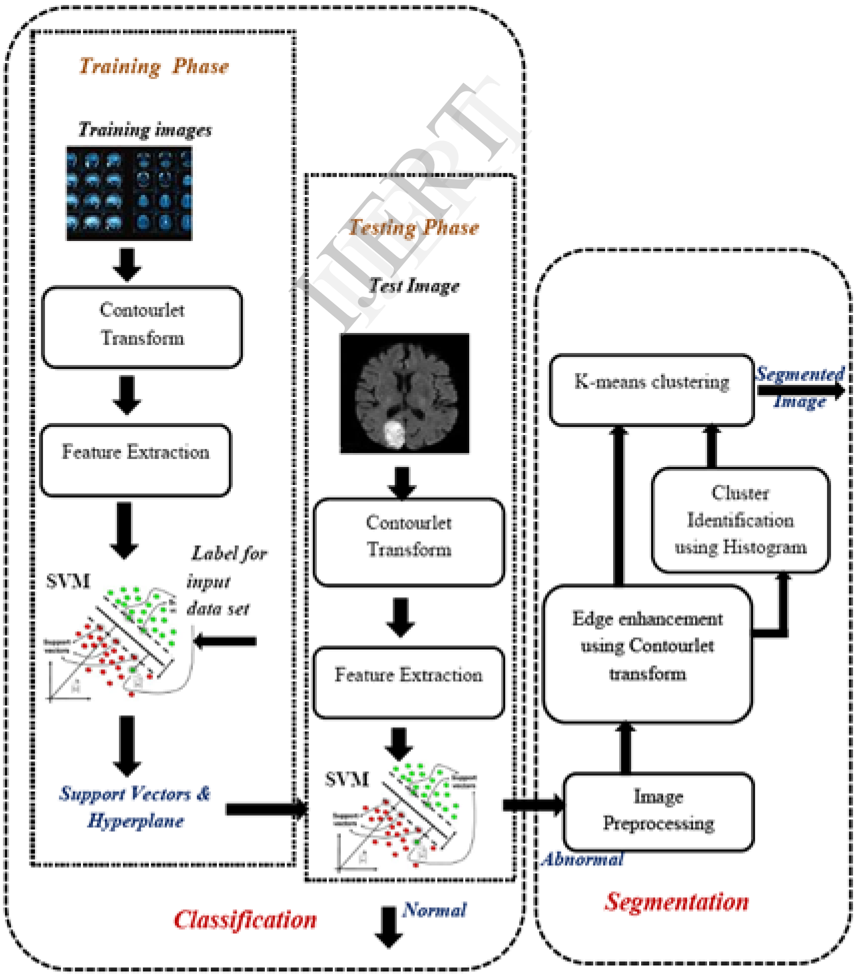


Figure 1.Block Diagram of Proposed Method

Here first step is the feature extraction of the training data set using Contourlet transform and co-occurrencematrix. In training phase, contourlet co-occurrence texture features of diffusion weighted images along with the label corresponding to the query images (label 0 for normal image and label 1 for abnormal image)are given as input to the classifier. In this paper, Support Vector Machine (SVM)[13,14]is used as the classifier as it gives better accuracy and performance than other classifiers. In testing phase, if the feature vector of new slice is given as input to the classifier, a well-trained classifier can accurately classify it according to the parameters(optimum hyperplane and support vectors) formed in the training phase.

A. Contourlet Transform

Contourlet Transform is a new multiscale and multidirectional technique proposedby Do and Vetterli. It captures edges and smooth contours at any orientation [12]. This scheme is implemented by using fillterbanks. This technique decouples the multiscale and directional decompositions which is handled by a Laplacian pyramid and a directional filter bank (DFB)respectively. The point discontinuities are first captured by laplacian pyramid (LP) and then followed by a directional fillter bank (DFB) to link the discontinuities into linear structures. The structural design of contourlet via laplacian pyramid and directional fillter is as follow: There are four frequency components of the input image like LL(Low Low), LH (Low High), HL (High Low) and HH (High High).At each level, the laplacian pyramid produces a low pass output (LL) and a band pass output (LH, HL,HH).And then the band pass output is passed into directional fillter bank, which results in contourlets coefficients. After that the low pass output is again passed through thelaplacian pyramid to obtain more coefficients and this process is repeated until the finedetails of the image are retrieved.For each image,at level one,2 and at level two,4 subbands are created This process is shown in the Fig2.

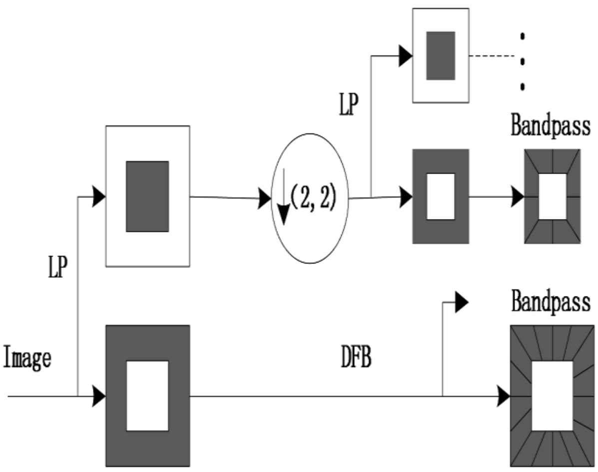


Figure 2.A flow graph of the Contourlet transform.

B. Feature Extraction

Features are said to be properties that describes the whole image. Texture feature extraction is found to be very important for further classification as the tissues present in the brain are difficult to classify using the shape or the grey-level intensities [15]. 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 [15].The extracted features act as input to the classifier. In the present work,features from the co-occurrence matrices of high frequency subbands are used since these subbands represents most clearest appearance of the changes between different textures.

The gray level co-occurrence matrix (GLCM)is a way of extracting second order statistical texture features. GLCM was defined as a matrix of frequencies at which two pixels (in specified direction and distance) occur in the image [16].The gray level co-occurrence matrix is defined as follows.

$$\varphi(d,\theta)=\left[P\left(i,j\middle|d,\theta\right)\right],0<i\le N_g,0<j\le N_g \qquad (1)$$

Where N_g is the maximum grey level. The function $P\left(i,j\middle|d,\theta\right)$ is the probability matrix of two pixels, which are located within an inter-sample distance d and direction θ have a gray level i and gray level j.Haralick introduced fourteen features from the GLCM and out of these fourteen features, four of the textural features are considered to be most relevant for our method. Those features are Energy, Contrast, Correlation and Homogeneity. They are defined in (2)-(5) where $\mu_x,\mu_y,\sigma_x,\sigma_y$ are the mean and standard deviationsof marginal distributions associated with $P(i,j)/R$ and R is a normalizing constant [16].

- Energy

Itis also called Angular Second Moment (ASM) where measures textural uniformity. High energy values occur when the gray level distribution has a constant or periodic form.

$$Energy=\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\left(\frac{P(i,j)}{R}\right)^2 \qquad (2)$$

- *Contrast*

It is a measure of local gray level variations in the image. This parameter takes low value for a smooth image and high value for a coarse image.

$$Contrast=\sum_{n=0}^{N_g-1}n^2\left\{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\left(\frac{P(i,j)}{R}\right)\right\},\quad |i-j|=n \qquad (3)$$

- Correlation

It measures the linear dependency among neighboringpixels. It gives a measure of abrupt pixel transitions in the image.

$$Correlation=\frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}[ij\,P(i,j)/R]-\mu_x\mu_y}{\sigma_x\sigma_y} \qquad (4)$$

- *Homogeneity*

It returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM.

$$Homogeneity=\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{1}{1+(i-j)^2}\left(\frac{P(i,j)}{R}\right)^2 \qquad (5)$$

1) Algorithm for Feature Extraction

Step 1: Decompose input image using 2-D Contourlet transform.

Step 2: Derive Co-occurrence matrices for high frequency sub bands of DWT with 1 for distance and 0; 45; 90 and 135 degrees for θ and averaged.

Step 3: From these co-occurrence matrices, four Haralick texture features called Contourlet Co-occurrence Texture features are extracted.These features are given as input to the SVM classifier.

C. Classification using Support Vector Machine

Support Vector Machine (SVM) is a powerful binary supervised classifier and accurate learning technique. It is very suitable for nonlinear classification. Here the basic idea is to map feature vectors nonlinearly to another space and learn a linear classifier there. The linear classifier in new space would be an appropriate nonlinear in the original space. Kernel functions effectively map the original feature vectors into higher dimensional space without explicit calculation. There are many types of kernels are available for SVM and this work uses the following kernels:Linear, Polynomial, Quadratic, Radial Basis Function [10,11].
SVM classify the input image into either normal or abnormal. If it is abnormal, Segmentation stage is performed to extract the ischemic stroke lesion from the abnormal image.

D. Segmentation

Image segmentation is a process of partitioning a digital image into multiple segments to change the representation of the image into something that is easier to analyse [17]. In the proposed method, K-means clustering [18] is used for segmentation because of its simplicity and computational efficiency. It is an unsupervised method because it does not use the training data. Before applying K-means clustering algorithm, Pre-processed Input image is sharpened using contourlet transform and number of clusters is selected from the peaks of the image histogram after smoothening as explained below.

1) Image preprocessing

Skull removal is very essential pre-processing task for accurate segmentation of abnormality from Diffusion Weighted Images since intensity of skull shares similar gray level values with certain brain structures. Different steps in skull removal as shown in Fig.3. It is done by Global thresholding using Otsu's method [19] due to large variation of back ground and foreground of the DWI. Here, pixels that are inside the brain boundary are

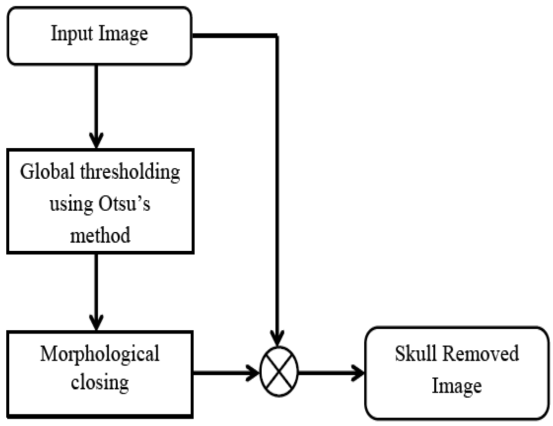


Figure 3.Process of skull removal

assigned as 1 (white) while the rest are set to 0 (black) as background.Perform morphological closing on the binary image with the Structuring Element (SE). By multiplying this binary image to the original image, the skull removed image is obtained with background value equals to zero.

2) Edge enhancement using Contourlet transform

High pass sharpened image can be obtained using Contourlet transform which provide good result for accurate segmentation. Different steps are given below

Step1: Apply two-level contourlet decomposition on pre-processed DWI using 'pkva' Pyramidal filter and 'haar' Directional filter which results one low pass subband and six bandpass directional subbands.

Step 2: Set low pass subband coefficients equal to zero.

Step 3: Apply inverse contourlet transform from the remaining bandpass directional subbands coefficients.

Step 4:Add the resulted image from step 3 to the preprocessed image to get a sharpened image.

3) K-Means Clustering Algorithm

Different steps involved in the K-means clustering algorithm are explained below[18].

Step 1:Pick K cluster centers.These points represent initial group centroids. Value of K is calculated from image histogram.

Step 2:Assign each pixel in the image to the cluster that minimizes the distance(Euclidean distance) between the pixel and the cluster center.

Step 3:Re-compute the cluster centers by averaging all of the pixels in the cluster.

Step 4:Repeat Steps 2 and 3 until the centroids no longer move.This produces a separation of the objects into groups from which the metricto be minimized can be calculated.

The objective function to be minimized is:

$$j = \sum_{j=1}^{K}\sum_{i=1}^{n}\left\| x_i^{(j)} - c_j \right\| \quad (6)$$

Where $\left\| x_i^{(j)} - c_j \right\|$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j, is an indicator of the distance of the *n* data points from their respective cluster centers.

III. RESULTS AND DISCUSSIONS

The Diffusion Weighted Images of 30 patients (22 abnormal and 8 normal) have been acquired from the Pushpagiri Medical College,Thiruvalla using 1.5T MRI GE scanners. Acquisition parameters used were time echo (TE), 82.6ms; time repetition(TR), 4700ms; pixel resolutions, 256 X 256; slice thickness, 5 mm; intensityof diffusion weighting known as b value,1000 s/mm^2.Images were encoded in 16-bit DICOM (Digital Imaging and Communications in Medicine) format. The input data involved 240Diffusion weighted images,120 normal and 120 abnormal. The abnormal brain images set consist of images of ischemic stroke. This algorithm has been implemented using Matlab R2010b.Detailed descriptions of experimental results in various stages aregiven below.

A. Classification

In classification phase, out of 240 images, 60 normal and 60 abnormal images are used for training and remaining 120 images are used for testing. In feature extraction stage, four features are extracted from the co-occurrence matrix of each high frequency subbands. These feature vectors are given as input to SVM classifier.Comparativestudy of classification performance of the SVM classifier has been made with different Contourlet decomposition level. Four types of kernel functions are used for Performance analysis of each level on the basis of accuracy and execution time as shown in Table 1.It is clear that features extracted using both pkva pyramidal filter and directional filter provides100% accuracy for all kernel function at level 2 & level 3.By considering execution time, it has been found that features extracted at level 2, classified with SVM RBF kernel function found to be best for classification.Comparativestudy of classification performance of the SVM classifier also has been made with individual features so that it can reduce feature vector dimension from 16 to 4.Results are shown in Table 2.

TABLE 1: Performance evaluation of SVM classifier

Contourlet decomposition level(using pkva filter)	Kernel Function	Accuracy (%)	Execution Time (Seconds)
Level 1	Polynomial	99	0.545
	Quadratic	99	0.554
	Linear	98	0.521
	RBF	92	0.242
Level 2	Polynomial	100	0.562
	Quadratic	100	0.586
	Linear	100	0.539
	RBF	100	0.272
Level 3	Polynomial	100	0.692
	Quadratic	100	0.712
	Linear	100	0.682
	RBF	100	0.321

TABLE 2: Performance evaluation of SVM classifier with individual features

Features used	Kernel Function	Accuracy (%)
Energy	Polynomial	100
	Quadratic	100
	Linear	100
	RBF	100
Contrast	Polynomial	100
	Quadratic	100
	Linear	100
	RBF	100
Correlation	Polynomial	86.2
	Quadratic	83.1
	Linear	82.2
	RBF	91.2
Homogeneity	Polynomial	100
	Quadratic	100
	Linear	100
	RBF	100

B. Image Preprocessing

Results of Image preprocessing are shown in Fig 4.A binary image has been obtained by applying Global thresholding using Otsu's method. Algorithm automatically calculates a suitable threshold value depending on the image. Morphological closing has been applied on the binary image to get the closed image. Here disk-shaped structuring element with radius 30 has been found to be the best based on experiments. Skull removed image is obtained by multiplyingthe closed image with original image.

C. Edge enhancement using contourlet transform

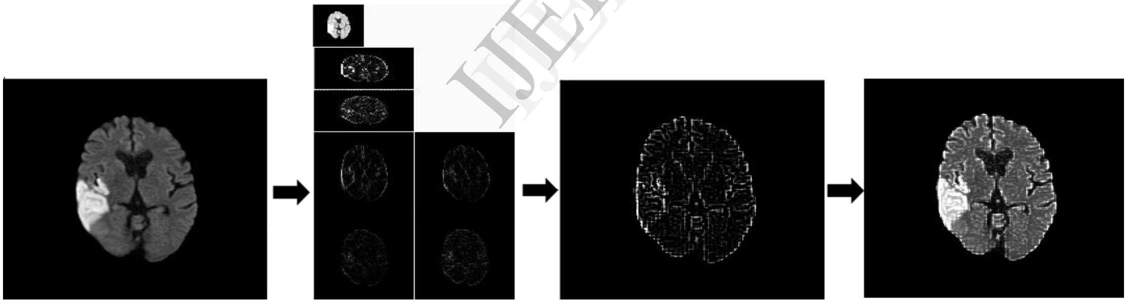
In this stage, Skull removed image is used as the input image. Second level contourlet Decomposition has been applied on the input image using pkva pyramidal filter and haar directional filter as shown in Fig 5.

D. K-means Clustering

K-means clustering is performed on the sharpened image to get the clustered image as shown in Fig 6. As the histogram of the given image has three peaks after smoothening, Number of clusters selected for the K-means algorithm is three. Since ischemic stroke lesion have high intensity compared to other tissue in DWI, a cluster with maximum intensity value has been extracted toobtain segmented ischemic stroke lesion.

(a) Input image (b) Binary image (c) Closed image (d) Skull removed image

Figure 4.Experimental Results-Image preprocessing



(a) Input image (b) Contourlet decomposed image (c) Detail image (d) Sharpened image

Figure 5.Experimental Results-Edge Enhancement

(a) Input image (b) Clustered image (c) Segmented image

Figure 6.Experimental Results-K-means Clustering

IV. CONCLUSIONS

In this paper, anovel approach is developedfor classifying DWI into either normal or abnormal and then segmentation of ischemic stroke lesion from the abnormal image.Features are extracted from the co-occurrence matrix of the high frequency contourletcoefficientsusing pkva pyramidal filter and pkvadirectional filter and classified further using SVM classifier.In the present work, fourof the textural features suchas Energy, Contrast, Correlation and Homogeneity are used.Different Contourlet decomposition level and kernel functions are used for performance analysis.On implementation, it is found that SVM RBF kernel function at second level Contourlet decomposition shows 100%accuracy with least execution time of 0.272 seconds.Classification performed using four features individually found to be efficient than four features together so that it can reduce feature vectordimension.K-means clustering is used for Segmentation purpose.Future works include development of the proposed algorithm using multi directional shearlet transform.

ACKNOWLEDGMENT

The authors wish to thank faculties in Radiology Department of Pushpagiri Medical College, Thiruvalla for providing dataset for this work.We alsothankall those who have guided in the successful completion of this endeavour.

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