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Mild Brain Injury Detection Using Texture Features

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Abstract— Mild Brain Injury (MBI) is defined by any disruption of brain function. The long lasting MBI related symptoms have not resolved completely. It can be resolved by treated immediately. So the early detection of mild injuries is very essential. Magnetic Resonance Imaging (MRI) is used for the detection of brain abnormalities. MBI is difficult to detect because it appears as the low contrast regions of MR Images. This work presents an automated detection of mild brain injuries in MRI using texture analysis and a suitable classifier.MR Images of tissue contains a lot of microscopic information that may not be assessed visually and texture analysis provides the means for obtaining this information. It mainly consists of two stages. Texture feature extraction and feature classification. The extracted features are given as input to SVM classifier. The classifier classify image between lesion and normal.

Keywords Magnetic resonance imaging, Mild brain injury, Texture analysis, Support vector machine classifier.

INTRODUCTION

Brain imaging is a widely used medical application that is helpful in the detection of brain abnormalities. Magnetic Resonance Imaging (MRI) is a procedure used in hospitals to scan patients and determine the severity of certain injuries. An MRI uses a magnetic field and radio waves to create detailed image of the body. MRI is examined by radiologist based on visual interpretation of the film to identify the presence of abnormal tissue. Brain images have been selected for the image reference for this work because the injuries of the brain tend to affect large areas of the brain.

Mild Brain Injury (MBI) is a disease that is commonly caused by a significant blow to the head from a sports related injury, motor vehicle accident, an accidental fall, or an assault. It is evidenced by loss of consciousness, loss of memory of events before or during the trauma, or a change in emotional or mental state at the time of the accident [1]. To be classified as mild brain injury, the patient must not experience post-traumatic amnesia for more than 24 hours, and loss of consciousness, if any, may not be longer than 30 minutes. Long lasting outcome of mild brain injury related symptoms cannot be resolved completely. The best outcome occurs when the MBI is treated immediately. So this is the need for the detection mild brain injury. Recently manual studies are used to identify the location and size of lesion from MRI. But the manual detection of mild injury is often difficult and require a lot of time and it is affected by inter and intra operator variability. Operator fatigue also plays a large role since manual detection can take a long time to analyze. However manual detection is still considered as a reference and automated algorithms are compared to this standard.

Currently there is a lack of computational methods for the evaluation of mild brain injury from MRI. This is because of the subtle nature of its progression and also it appears in the low contrast regions of images. Here uses the texture analysis of the images. MR Images of tissue contain a lot of IJERGS staff will revise and reformat if requiredmicroscopic information that may not be assessed visually and texture analysis technique provides the means for obtaining the information and it is used to detect structural abnormality in each tissue. The goal is to find an accurate method for this purpose.

Mild Brain Injury is difficult to detect as it appears in the low contrast regions of MR Images[3]. It involves textural analysis of MR Images and a suitable classifier. In medical image analysis the determination of tissue type and classification of tissue abnormality are performed by using texture. Textural analysis is used to detect structural abnormality in each tissue. Textural features are used as input to classifiers in order to provide an information about lesion versus non lesion region[10]. Textural feature extraction methods are used for the extraction of features. A support vector machine classifier provides the locations of lesion.

METHODOLOGY

Mild Brain Injuries (MBI) are located at the low contrast regions of MR images. Detection of such abnormalities are difficult because of the subtle nature of its progression and low contrast appearance. Current abnormality detection approaches uses feature extraction and classification as the major steps. The accuracy of the detection depends on the type of classifier used. It combines the advantages of texture features and a suitable classifier. Databases of known injured images are taken as the reference for the accurate detection.

This method consists of two stages. Feature extraction and feature classification. All the images are MRI T2 weighted images with different views but the same resolution. The T2 weighted images shows clearer vision than other modalities. The images undergo a feature extraction process. Textural features are considered for the purpose of mild injury detection because texture features are able to identify micro structural changes that occur in the brain. The next step is the feature classification. Classifiers are used to estimate the locations of lesion and the normal appearing brain matter space. This approach performs well when there is a large amount of training data. It estimates the lesion using only visual features. The block diagram for mild injury detection is shown in Figure 1.

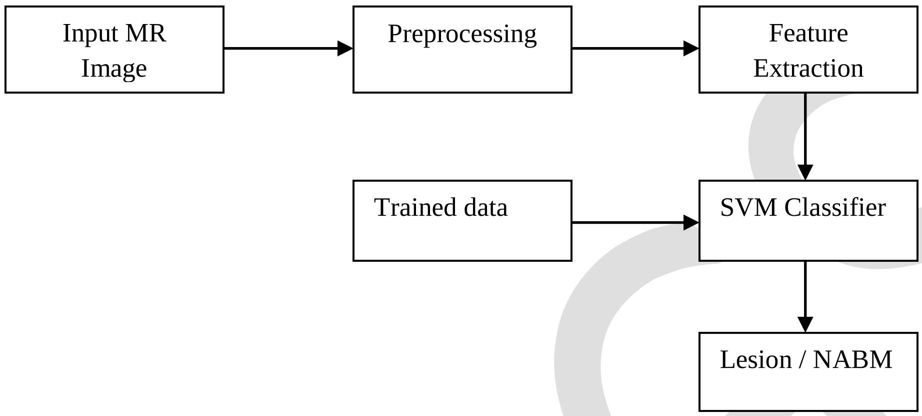

Figure 1: Block diagram of mild brain injury detection

1.PREPROCESSING

Image preprocessing is an essential procedure and the simplest categories of medical image processing .This stage are used for reducing image noise, highlighting edges, or displaying digital images. These are used to suppress noise and imaging of spectral parameters. After this stage the medical image is converted into standard image without noise[11]. Preprocessing techniques are used to improve the detection of the suspicious regions in MRI. Here the preprocessing method consists of three steps: First, the image is converted to gray scale image. Second, a median filter is used to reduce noise. Third, image equalization is applied to smooth the gray level image with an average value.

The median filter is the simpler technique and it removes the speckle noise from an image and also removes pulse or spike noise. The Median Filter is performed by taking the magnitude of all of the vectors within a mask and sorting the magnitudes. The pixel with the median magnitude is then used to replace the pixel studied.

Adaptive histogram equalization is used for enhancing the contrast of an image. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image and uses them to redistribute the lightness value of the image. It is therefore suitable for improving the local contrast of an image and bringing out more detail.

2. FEATURE EXTRACTION

Feature extraction is a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. Transforming the input image into a set of features is called feature extraction. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete the tasks[12]. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. Texture based feature extraction methods are used for this work. Image texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image. Texture can be defined as a descriptor of local brightness variation from pixel to pixel a local neighborhood of an image[13]. In general texture can be defined as the neighborhood property of an image. Mild injury causes texture changes in the brain with features based on region histogram statistics, co-occurrence matrix and gradient measures.

2.1 Histogram based features

The histogram-based features used in this work are first order statistics that include mean, variance, skewness and kurtosis. Let z be a random variable denoting image gray levels and p(zi), i = 0,1,2,3,.L-1, be the corresponding normalized histogram, where L is the number of distinct gray levels. The features are calculated using the above-mentioned histogram.

Mean: It gives the average gray level of each region and it is useful only as a rough idea of intensity not really texture.

$$m = \sum_{i=0}^{L-1} z_i \; p(z_i)$$

Variance: It gives the amount of gray level fluctuations from the mean gray level value.

$$\mu_2(z) = \sum_{i=0}^{L-1} (z_i - m)^2 p(z_i)$$

Skewness: It is a measure of the asymmetry of the gray levels around the sample mean. If skewness is negative the data are spread out more to the left of the mean than to the right. If skewness is positive, the data are spread out more to the right.

$$\mu_3(z) = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i)$$

Kurtosis: It is a measure of how outlier-prone a distribution is. It describes the shape of the tail of the histogram. That is it describes the measure of flatness of the histogram.

$$\mu_4(z) = \sum_{i=0}^{L-1} (z_i - m)^4 p(z_i)$$

2.2 Co-occurrence based features

Gray Level Co-Occurrence Matrix (GLCM) has proved to be a popular statistical method of extracting textural feature from images and it is a widely used texture analysis method. It enhances the details of image and gives the interpretation.The GLCM is a tabulation of how often different combinations of pixel brightness values (gray levels) occur in an image. The advantage of the co-occurrence matrix calculations is that the co-occurring pairs of pixels can be spatially related in various orientations with reference to distance and angular spatial relationships, as on considering the relationship between two pixels at a time. As a result the combination of grey levels and their positions are exhibited apparently.

An image of GLCM (i ,j)extracts the features based on pixeland its next neighbor pixel in the image. GLCM (i, j) is a two dimensional function and it is composed of m pixels in the vertical direction and n pixels in the horizontal direction. i, j are horizontal and vertical co -ordinates of the image. The total number of pixels in the image is m*n = N, where i varies from from 0 to m and j varies from 0 to n.The features that are obtained by using the GLCM matrix are:

Contrast: It measures the intensity contrast between a pixel and its neighboring pixel over a whole image. It is zero for constant images.

$$contrast = \sum_{i=0}^{m} \sum_{j=0}^{n} (i - j)^2 GLCM\,(i, j)$$

Energy: It is a measure of uniformity through an image and it is the sum of squared elements in a GLCM. It is one for constant images.

$$energy = \sum_{i=0}^{m} \sum_{j=0}^{n} GLCM(i, j)$$

Homogeneity: The closeness of gray levels in the spatial distribution over image is inferred by homogeneity. Homogeneous textured image is comprised of limited range of gray levels and hence, the GLCM image exhibits a few values with relatively high probability.

$$homogeneity = \sum_{i=0}^{m}\sum_{j=0}^{n}\frac{GLCM(i,j)}{|1+(i-j)|}$$

Correlation: Correlation that brings out how correlated a referencepixel to its neighbor over an image. It is uncorrelatedto energy, contrast and homogeneity. It measures howa pixel is related to its neighbor pixel.

$$correlation = \sum_{i=0}^{m}\sum_{j=0}^{n}\frac{(i*j)GLCM(i,j)-\left(\mu_x\mu_y\right)}{\sigma_x\sigma_y}$$

2.3 Gradient based features

An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. Gradient images are created from the original image by convolving with a filter. One of the simplest filter used for this purpose is the Sobel filter. Each pixel of a gradient image measures the change in intensity of that same point in the original image, in a given direction. To get the full range of direction, gradient images in the x and y directions are computed[10]. A gradient image in the x direction measuring horizontal change in intensity and a gradient image in the y direction measuring vertical change in intensity. Gray pixels have a small gradient and black or white pixels have a large gradient.

3. SUPPORT VECTOR MACHINE CLASSIFIER

Classification analyses the numerical properties of image features and organize the data into different categories. It mainly consist of two phases. Training phase and testing phase. Classification is the process where a given test sample is assigned a class on the basis of knowledge gained by the classifier during training. To make the classification results comparable and for exhaustive data analysis, we have usedleave one out classification method for the SVM classifier.

The Support Vector Machine(SVM) classifier is trained by using the features obtained from the lesion and non-lesion region. Manual segmentation is taken as the ground truth forthe finding lesion region. Here the lesion region is obtained by cropping or similar intensity grouping operation. Then trained the classifier by using the features obtained from thetwo region. After the training operation test the classifier performance by using a new input image.

Support Vector Machine is a discriminative classifier formally defined by a separating hyperplane. In other words,given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. The operation of the SVM algorithm is based on finding the hyperplane that gives the largest minimum distance to the training examples. Twice this minuimum distance gives the maximum margin. Therefore, the optimal separating hyperplane maximizes the margin of the training data. This decision boundary optimally separates two classes of input data points. This decision boundary is shown in figure.2 where M is the maximum margin, that is the distance of the hyperplane to the nearest point of the two classes. The equation for the hyperplane is given by

$$y = w^T x + b$$

Where w is known as the weight vector and b is the bias. Theoptimal hyperplane can be represented in an infinite numberof different ways by scaling of w and b . As a matter of convention, among all the possible representations of thehyperplane, the one chosen is

$$|w^T\ x + b| = 1$$

Where x symbolizes the training examples closest to the hyperplane. In general, the training examples that are closest to the hyperplane are called support vectors. This representation is known as the canonical hyperplane.The distance between a point x and a hyperplane is given as

$$distance = \frac{|w^T x + b|}{\|w\|}$$

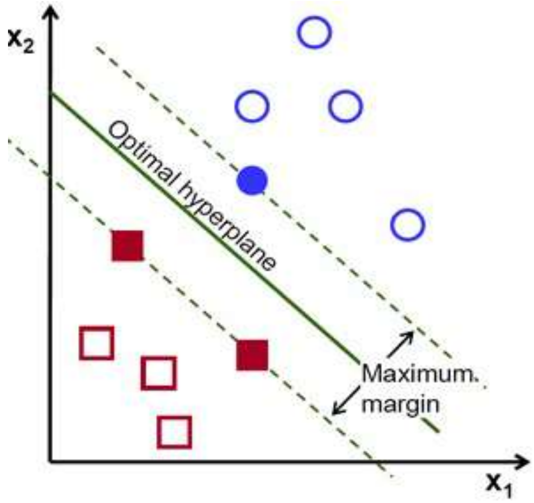

Figure2: SVM for classifying datapoints

In particular, for the canonical hyperplane, the numerator is equal to one and the distance to the support vectors is

$$distance = \frac{1}{\|w\|}$$

The distance of the hyperplane to the nearest point of thetwo classes is given by

$$M = \frac{2}{\|w\|}$$

Finally, the problem of maximizing M is equivalent to the problem of minimizing a function L(w) subject to some constraints. The constraints model the requirement for the hyperplane to classify correctly all the training examples x_i .Formally

$$\min_{w,b} L(w) = \frac{1}{2}\|w\|^2 \ subject\ to\ y_k(w.x_k - b) \geq 1\ \forall i$$

Where $y_k$represents each of the labels of the training examples. In nonlinear SVM the data points are not always be separated by drawing a straight line. In such situations the data points in input space are transformed to a higher dimensional space by using a kernel function. Many kernel functions are used for SVM such as linear, polynomial, radial basis function and sigmoid etc.

RESULTS

The dataset consist of T2 weighted MR Images having micro lesions. T2 images are of higher contrast and clearer vision as compared to other modalities. All the images are resized to 256 × 256 for further processing. First the image is converted to gray scale images. Figure 3 shows the re sized gray scale input image.Preprocessing stage includes noise removal and contrast enhancement. Median filter is a good choice for removing noise from MR Images. It is best suit for removing certain type of random noise from the images. Figure 4 shows the filtered image. Adaptive histogram equalization is used for improving the contrast of an image. Figure 5 shows the equalized image.

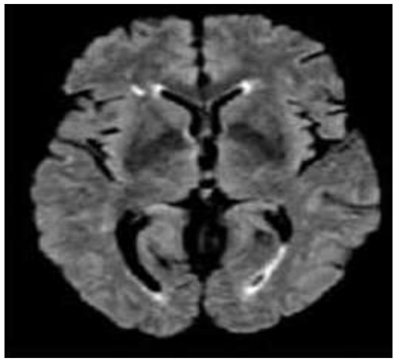
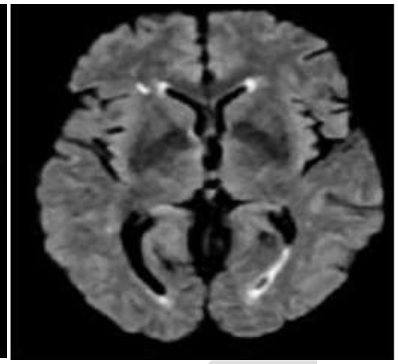

Figure 3 : Resized input image   Figure 4: Filtered image

Feature is a property that represents the whole image. Here texture features are used. In the training stage features from the lesion and non-lesion regions are taken. According to this features further classification is done. Three methods are used for extracting features from the images. All the extracted features act as input to SVM classifier. It consist of two stages, a training stage and a testing stage. Classifier is trained according to the features obtained from the lesion and non-lesion regions. In the testing stage the classifier performance is analyzed by using a new image having mild injury. At the output of the classifier the correct region is detected.

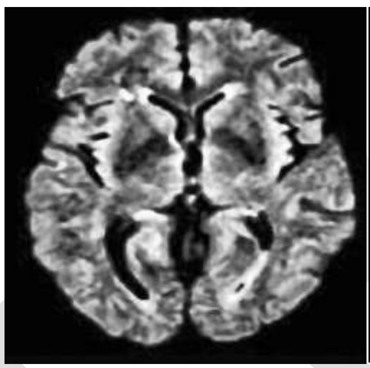


Figure 5: Contrast enhanced image   Figure 6: Lesion detected image

CONCLUSION

Automatic brain abnormality detection mainly involves two steps. Feature extraction and feature classification. Selectionof these two are depends on the specific application. Mild brain injury is difficult to detect because it appears in the lowcontrast regions in an image.It is a fully automated method for detecting mild brain injuries that uses texture analysis and classification. Texture analysis is used for obtaining the microscopic information from the images that may not be assessed visually. Here we are combining the texture featuresand a suitable classifier to produce a posterior probability oflesion. Detection accuracy can be with the help of large database and features.

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