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An Improved Local Ternary Pattern Based Tumour Classification of MRI of Brain

[1]R. Meenakshi and [2]P. Anandhakumar
[1]Saveetha Engineering College, Thandalam, Chennai 392/2, Green Gardens, 'L' Block, Anna Nagar East, 600102 Chennai, India
[2]Department of C.T, M.I.T Campus, 44 Chennai, India

Abstract: A tumor (American English) or tumour (British English) is commonly used as a synonym for a neoplasm that appears enlarged in size. Neoplasm is an abnormal mass of tissue as a result of abnormal growth or division of cells. This tumor may be solid or fluid-filled. It can occur even in the brain. As the brain is well protected by the skull, early and in-depth detection techniques are needed for the identification of brain tumors which is one of the challenging tasks. Magnetic Resonance Imaging (MRI) technique is mainly used for analyzing the brain as the images produced are of high precision and applicability. Most of the tumour identification methods make use of different machine learning and segmentation techniques to provide improved detection accuracy. The challenge lies in accurate diagnosis in spite of improved existing techniques. The objective of the proposed research is to classify the brain MRI dataset for the existence or non existence of tumors. The proposed method uses Multilevel Local Ternary Pattern (MLTP) for pattern string generation. This is grouped for faster processing and for further classification using Support Vector Machine (SVM). The generation of pattern string gives the classification accuracy of 96% when compared to the existing classification techniques.

Key words: Tumor, neoplasm, Magnetic Resonance Imaging (MRI), diagnosis, existence

INTRODUCTION

Brain tumor: Tumor can be cancerous or non cancerous. The diagnosis of brain tumor is best done by MRI since through this imaging technique not only the early stages but also advanced stages can be detected (Gopal and Karnan, 2010). The treatment of brain tumors depends on type, size and location of tumor. The cause of brain tumor still remains unknown but research has established some risk factors which remain only a few. For example, when children are put to radiation in the head they have equal probability of getting brain tumors as that of adults. Genetic and age are also some other risk factors.

The Local Ternary Pattern Operator (LTPO) approach (Tan and Triggs, 2010) examines the similarity among the pixels. Pixels with slight variations were considered alike and the degree of similarity were judged with threshold value t. Local Ternary Pattern (LTP) considered eight nearest neighbors of each pixel and used the concept of "uniform" patterns. The gray level difference x between the pixels around eight neighbors was checked against a threshold value t and was represented as in Eq. 1:

$$y(x)=\begin{cases}0 & x<t\\ 1 & -t\le x\le t\\ 2 & x>t\end{cases}$$

The gray-scale invariance was achieved by means of determining the y value by comparison instead of using their exact values. The y value was not be affected by shift in the gray values. Figure 1a shows the y values calculation along the border of a 3×3 local region and

(a)

124	138	145
126	129	134
137	45	127

(b)

1	2	2
1		1
2	0	1

Fig. 1: A 3×3 region and its pattern matrix; a) region of 33 considered and b) pattern matrix generated using LTP

Corresponding Author: R. Meenakshi, Saveetha Engineering College, Thandalam, Chennai 392/2, Green Gardens, 'L' Block, Anna Nagar East, 600102 Chennai, India

Fig. 1b its pattern matrix generated using Local Ternary Pattern. A Pattern String was formed from the Pattern matrix by collecting the y values starting from any position. The generated string for Fig. 1 was Generated Pattern String 2 2 1 1 0 2 1 1.

The MLTP operator finds the association of LTP operators at multiple levels in a squared neighborhood to identify the macro features and also examines the similarity among the pixels. Pixels with slight variations in their values have been considered alike and the degree of similarity has been judged with a threshold value.

Literature review: Chaplot *et al*. (2006) have classified brain MRI using the combination of wavelets, SVM and artificial neural networks. Self organizing map was used for Artificial Neural Networks (ANN). This combination gave accuracy of 98% classification. The researchers had used only 52 MRI but the proposed research used 172 images. Selvaraj *et al*. (2007) have classified brain MRI slices using least square support vector machines. Researchers derived features from the slices and uses linear and non linear Radial Basis Function (RBF) for classification. The classification gave a result of 98% of accuracy but the researcher does not consider time factor as done in the proposed research. El-Emary and Ramakrishnan (2008) have suggested the use of Probabilistic Neural Network (PNN) to classify brain tissues in multiple sclerosis. Their modified PNN took 3.622 sec as against the proposed research which takes only 0.99 sec only.

Majos *et al*. (2004) have classified the brain tumor using proton magnetic resonance spectroscopy which gave a result of 90% accuracy in its classification. Only 151 images were considered. Also, the comparison was between two different inputs obtained from spectra. Gerstle *et al*. (2000) have used neural network, Linear Discriminant Analysis (LDA) for analyzing magnetic resonance spectroscopy. This was used to classify head and neck squamous cell. The results achieved were 91%. Yamashita *et al*. (2008) used ANN classifying intra-axial cerebral tumors on MRI. They used 126 images and evaluation was done using Receiver Operating Characteristic (ROC). The improvement was 0.001%. Hamilton-Wright *et al*. (2007) have used pattern discovery algorithm for fuzzy classification. Researcher proved that the improvement to 0.03%. Luts *et al*. (2007) uses a mutli-class classification system for classification of MRI's for tumor. He makes use of least square support vector machine for this purpose. His comparison says that the performance of the multi class system was better than LDA.

The proposed approach takes into account associations between neighbouring cells and small change in values based on threshold are considered as one value. The number of images considered for processing is 172 images, the time taken for processing is less and the average classification accuracy is 98%.

MATERIALS AND METHODS

Proposed multi level LTP operator: In this proposed method classification of brain MRI is done using the combination of multilevel local ternary pattern and classification using SVM. Since, MLTP is a feature descriptor which examines similarity among pixels, it is combined with SVM for tumor classification in brain MRI. SVM is the most general classifier used for classification. Therefore when MLTP is combined with SVM the classification accuracy increase. Figure 2 shows the proposed MLTP of 5×5 operator.

This proposed research presents a method of find the pattern string from the image. The pattern strings are grouped in order to reduce the number of inputs that are given to SVM for classification. The result of this group for all the images is given to SVM as input. The performance of SVM classifier is measured in classifying tumour from non tumour images. The combination of MLTP with SVM classifier has been proposed in this study enabling proper classification thereby reducing the complexity involved and enhancing the processing time. The developed classification system is expected to provide a valuable and accurate classification process for the physicians. This proposed method gives a classification accuracy of 96% when compared with other conventional texture analysis methods.

The steps involved in MLTP pattern string generation for an image is given in Fig. 3. In Fig. 3 for each brain MRI, a 5×5 pixel set is considered. From this 5×5 set,

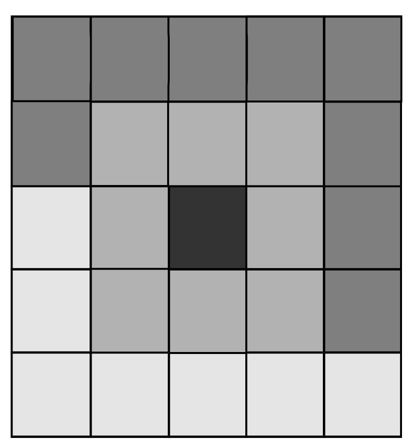

Fig. 2: Proposed multilevel ternary pattern

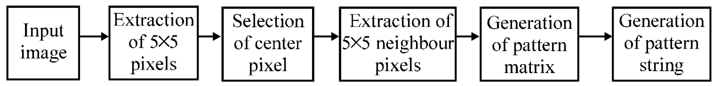

Fig. 3: Phases in LTP pattern string generation

the centre pixel is chosen which is compared with its eight neighbours. A threshold value is set which is either added (upper limit) or subtracted (lower limit) from the centre pixel. The threshold value is varied for measuring the similarity among the pixel in the image. The setting of threshold value inserts the idea of human perception. If the value of the neighbor considered is between these values then its value is set to 1. If the value of the neighbor pixel considered is less the lower limit then its value is 0 and if it is greater than the upper limit then the value is 2. This leads to the generation of pattern matrix from which the pattern string is generated.

Figure 4 shows the steps that the proposed study follows while classifying the tumor MRI from the database. From the dataset of brain MRI's, each image is considered for processing. The database consists of a total of 172 images. All the images are taken for training and testing. In these 172 images, 97 are tumor images and 75 are non-tumor images. The size of the images is 256×256. In each image a 5×5 matrix from the image is chosen for processing. The process is applied to whole of the image which is described in the algorithm. From the chosen 5×5 pixel matrix, a pattern matrix is generated and from this a pattern string for the considered 5×5 pixel set is generated. Depending on the size of the image and pixels considered pattern strings will be generated. In the proposed research the image size is 256×256 and the pixels set is 5×5 therefore the number of pattern strings generated is 104. Then, these patterns are grouped to reduce the size of the processed string. The processed result of all the images are given to SVM for training and then for classification.

The performance of the proposed technique in tumor identification is evaluated by using the positive and negative cases. This means if a brain MRI is one with tumor then it must be identified as a tumor image, i.e., True (T) and Positive (P). The other combinations in this include:

- True Negative (TN): in this case the given tumor image is not identified as one
- False Positive (FP): in this case the given non-tumor image is identified as one
- False Negative (FN): in this case the given non-tumor image is not identified as one

Using these cases the sensitivity, specificity and accuracy are defined as follows:

$$\text{Sensitivity} = \text{TP+FN} \tag{2}$$

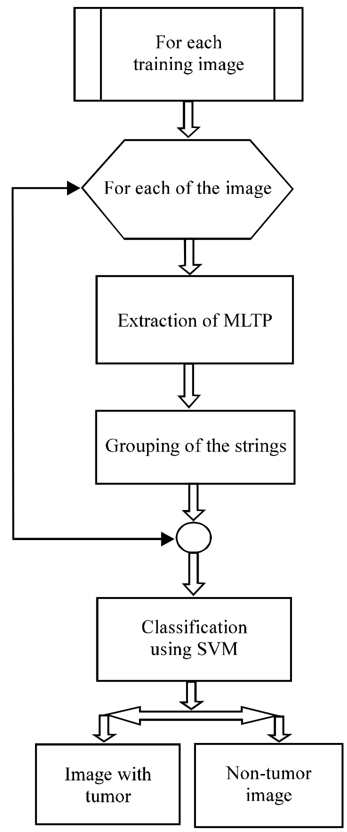

Fig. 4: System architecture

$$\text{Specificity} = \frac{\text{TN}}{\text{Total No. of tested images}} \tag{3}$$

$$\text{Accuracy} = \frac{\text{Sensitivity}}{\text{Total No. of tested images}} \tag{4}$$

$$\text{Total percentage of accuracy} = \text{Accuracy}\times 100 \tag{5}$$

The system architecture for multilevel local ternary pattern has been illustrated in Fig. 4.

The algorithm for tumor identification using MLTPO:

Input: Training images of brain MRI
Output: Classified result of brain MRI
1. For each training image:
   a. Perform block processing depending on operator size
   b. For each block of the training image
      i. Extract LTP code for octets
   c. Compute the pattern string
   d. Group the pattern string
   e. Classify it using SVM

Table 1: Percentage of accuracy and time taken for MLTP 5×5

Threshold value	No. of bins: 2		5		10		15		20	
	Accuracy (%)	Time (sec)	Accuracy (%)	Time (sec)	Accuracy (%)	Time (sec)	Accuracy (%)	Time (sec)	Accuracy (%)	Time (sec)
2	65.69	0.144	72.67	0.153	93.06	0.8020	98.83	0.965	100.00	0.650
5	66.86	0.996	76.16	0.226	95.93	0.7859	98.25	0.556	99.41	0.654
10	69.76	0.222	79.06	0.243	90.69	0.7790	100.00	0.784	99.41	0.645
15	65.69	0.178	78.48	0.259	96.51	0.8290	99.41	0.631	100.00	0.656
20	64.53	0.087	77.32	0.196	95.34	0.8860	99.41	0.756	100.00	0.671

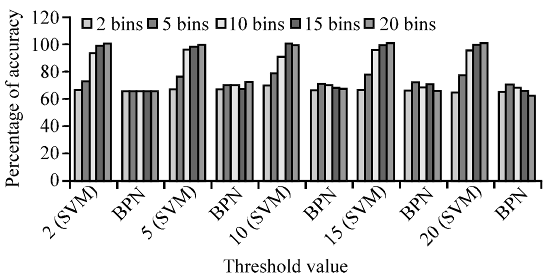

Fig. 5: The percentage of accuracy for various bin sizes and threshold values

RESULTS AND DISCUSSION

The evaluation metrics used as TP, FN, TN and FP for evaluating the percentage of accuracy in identifying the tumor in the given image. Here, TP means True Positive, FN means False Negative, TN True Negative, FP means False Positive. The combination of MLTP and classification is used to identify the tumor in a MRI of the brain. MLTP of size 5 and various threshold values and bin sizes have been used for evaluation. The grouping is done using the built-in hist operator which groups the whole pattern string space based on the values of the pattern string space. Therefore, instead of finding the features from the pattern string space the values are divided according to the bin size given and thereby reducing the length of the pattern string space which is given for further processing. Reduced pattern string space increases he classification accuracy. This result is given to SVM for classification of tumor in the image.

Table 1 shows the values of the percentage of accuracy and time taken for the same for the MLTP operator size 5×5. It also shows the percentage of accuracy and time taken in seconds for various sizes of the bins considered and the various threshold values for those bins. For example, for 15 bins having a threshold value 2 the percentage of accuracy is 98.83 and the time taken to achieve this accuracy is 0.965 sec. The total images considered are 172 out of which 97 are tumor images and 75 are non-tumor images which are identified correctly for the no of bins 15 and the threshold value 10. The same is achieved for no of bins-20 for the threshold value 2, 15 and 20. The increase in bin size increases the spread of values which in turn increases the classification accuracy (Fig. 5).

CONCLUSION

Tumor classification, tough job when done physically is made easy by automating it using the proposed work of combining multi level pattern generation with SVM for classification. The local ternary pattern is makes use of 3 bit values 0, 1 and 2 unlike local binary pattern which uses either 0 or 1 for classification. Therefore, in the proposed approach operators based on local ternary pattern has been used for tumor classification. It is also used for classifying Attention-Deficit/Hyperactivity Disorder (ADHD) in structural MRI data (Chang *et al*., 2012). The proposed research has made use ternary pattern string for classifying tumor in brain MRI. For comparison BPN classification was used. Even the BPN experiments were done for threshold values and bins sizes of 2, 5, 10, 15 and 20. The accuracy was only 72%. The study shows the percentage of accuracy for SVM and BPN for the considered threshold value and bin sizes.

The proposed technique is effective since it has produced a detection accuracy of 96% for the operator size 5×5 as a result of applying a pattern string on the image and combining it with SVM classification.

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