Brain Tumor Imaging Classification Based on Rounding off The Euclidean Distance Function

م.م باهرة هاني نايف
قسم هندسة تقنيات الحاسوب
كلية التراث الجامعة

م.م انغام خالد حسين
قسم هندسة تقنيات الحاسوب
كلية التراث الجامعة

المستخلص

المصنف (LVQ) Learning vector Quantization من التقنيات المستخدمة في تصنيف الصور الطبية. الهدف الرئيسي من هذة الدراسة هو تحسين المصنف (LVQ) لغرض الحصول على دقة عالية في تحديد الاورام الدماغية من MRI . في هذا البحث تمت دراسة تأثير تقريب قيم معادلة المسافة ل Euclidian . والمتجة المرمز الذي يبعد اقل مسافة عن المتجة الداخل يعين كمتجة مرمز فائز. ويتم اهمال بقية المتجهات المرمزة البعيدة عن المتجة الداخل. وبعد عدد معين من الدورات تصبح متجهات ميتة. تم استخدام ثلاث مجاميع من البيانات وهي صور للدماغ ، ومجموعتين من الصور المعالجة من من موقع UCI للبيانات. وتم مقارنة ثلاث انواع من المصنف LVQ وهم LVQ١, OLVQ٣, Multi-pass LVQ و Hierarchical LVQ . واظهرت الدراسة تحسن واضح جدا في الانحراف المعياري لجميع المصنفات المستخدمة.

ABSTRACT

Accurate early detection of brain tumors in different types one of the effective reasons of providing the required treatment. Using image processing techniques and machine learning classifiers are used to achieve fast and high accuracy recovery procedures.

In this paper discussed the effect of rounding off the Euclidean distance function of the classifier Learning vector Quantization (LVQ). In this case the some of the codebook vectors with minimum chances to be chosen in the early steps of training will not bushed away for the rest of the training process. If they pushed away they will be considered as dead codebook vectors and neglected.

The test data samples used are the brain tumor (MRI) for two kinds of patients normal and abnormal and UCI benchmark data sets. Comparison studies showed that the proposed method results are promising for LVQ1, OLVQ3, Multi-pass LVQ and Hierarchical LVQ. The results showed a very good improvement in the standard deviation of LVQ1 as well as the other classifiers.

Keywords : Magnetic Resonance Imaging, Learning vector Quantization , Rounding off, Euclidean distance function.

INTRODUCTION

Computer and information technology is widely used in medical images processing. It shortens the diagnosing time and improves the efficiency of the diagnosis. MRI technique is one of the tools used in clinical and surgical environment. MRI technique is preferred due to its characteristics such as superior soft tissue separation, high spatial resolution and contrast. In addition, no harmful ionizing radiation to patients. MRIs are examined manually by radiologist based on visual interpretation of the MRI slices to verify the presence of tumor abnormal tissue. The analyzing process consumes time due to the large number of MRIs per patient. In addition, the sensitivity of the human eye in interpreting large numbers of images decreases with increasing number of cases [1]. An automated normal and abnormal brain classification from magnetic resonance images (MRI) is of great field for research and clinical studies [2].

RELATED WORK

Recent researches proved that brain MRI classification is possible using supervised artificial neural network like LVQ, Multi Perceptron (MLP) and Radial Base Function (RBF) and unsupervised using Self-Organizing Map (SOM).

In Carlos et al. [3] study, the researchers apply LVQ classifier to classify simulated brain images and compare it with the phantom images to mask each tissue. The results of this study were good in terms of computational efficiency but the segmented images was not clear enough to distinguish between the external layers of the brain, as there's not a clear classification of tissues corresponding to scalp, skull and the external portion of Cavernous sinus CS. In Crammer, K., et al.[4] study , the researchers build a positioning prototype for generalization bounds using maximal margins principle with loss function to construct algorithms. LVQ classifier showed sensative and more special performance in comparing with Nearset Niebour (NN) classifiers.

On the other hand Kashtiban et al. [5] study proposed Discrete Wavelet Transformation, wavelet packet and featyre selection using a multivariate statistical method to select the best wavelet coefficients as feature vectors to input into the LVQ and Multiperceptron (MLP) classifier. In Rathi study [6] a novel method of feature selection and extraction was introduced. The researchers approach was combinding the intensity, texture shape based features and classifies the tumor region as white matter, Gray matter, CSF, abnormal and normal area. Dynamic features were selected using Linear Discriminant Analysis (LDA). The results were compared to Principal Component Analysis (PCA) dimension reduction techniques. The number of featres selected by PCA and the classification accuracy for SVM is 98.87%. Another study proposed by Deepa and Devi [7] using Back propagation neural network (BPN) and Raidal Basis Function Neural Network (RBF) to classifiy the optimal texture features extracted from normal and tumor regions of MRI by using statistical features. The results showed outstanding performance of RBFN algorithm when compared to BPN with classification accuracy rate equal to 85.7%.

In this paper LVQ classifier with rounding off the Euclidean is proposed to classify brain MRI into normal and abnormal.

THE EXPERIMENT

In this experiment a set of four members of LVQ classifier family are used with MRI images classification to test their performance with rounding off Euclidean distance function. These classifiers are LVQ1,LVQ2, MLVQ and HLVQ.

MRI images preprocessing

Extracting the important features of MRI images must be pass throught image preprocessing methods and techniques. Some of these techniques are applied to remove noise and sharpning the image while preserving the image edges and protect important information from lost. These methods are called image

enhancement techniques. In this paper two filters are used to clear and sharp the MRI images which are median filter with window size (3X3) and high pass filter. The next step is applying image segmentation techniquies to detect the tumor area then feature extracting. The steps are shown in Fig.1.

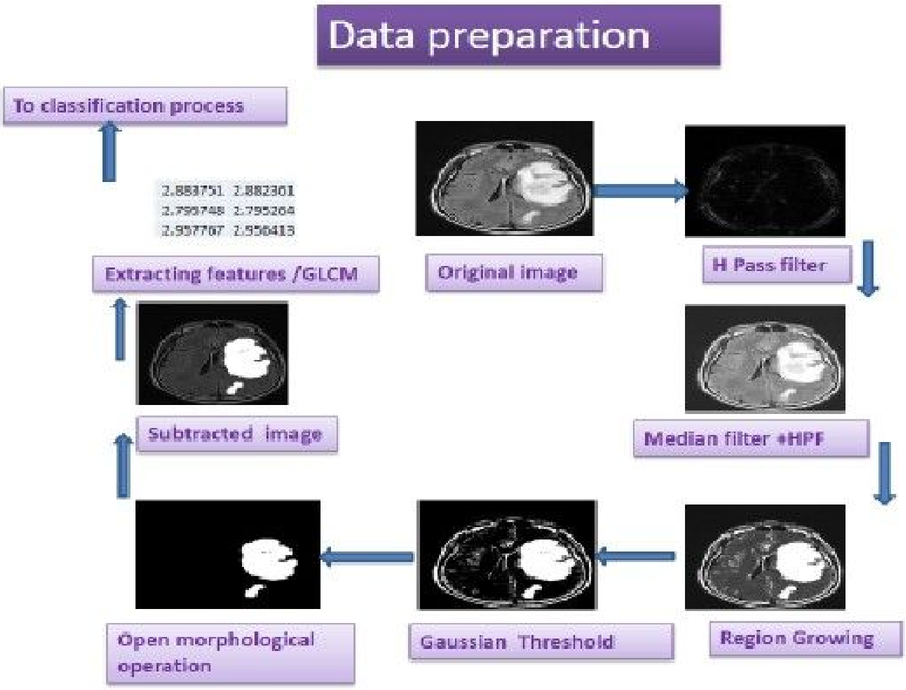

Figure 1 Brain Dataset preprocessing steps [10]

The proposed lvq classifier

Learning vector quantization (LVQ) is a supervised Artificial Neural network. It is a competitive learning technique that uses the training set to decrease the size of the hidden layer. It defines class boundaries prototypes, a nearest-neighbor rule. LVQ is consists of three layers: input layer, competitive layer and the output layer. Classes or patterns are mapped to target class in the output layer. The distance equation used to evaluate the distance between the input vectores and the knohanon layer vectors is the Euclidean distance function as in equation (1).The codebook vector with minimum distance is the winner neuron unlike the unchosen codebook vectors are considered as dead vectors and with no chance to contribute in future classification [8].

$$d_i = \| W_i - X \| = \left[\sqrt{(\sum_j W_{ij} - X_j)^2)}\right] \qquad (1)$$

The results of the Euclidean distance function varyies in a very small differences but the chossen winner vector will be the nearest only. The unselected code vectores will be totally nelected after few iteration in building training model [10]. These codebook vectores could play an important role in the farther iterations and neglect them in early stage of training could effect the classifier performance accuracy [8]. So, this study proposed rounding off the Euclidean distance function as shown in Fig.2 to give a chance to the pushed away codebook vectors to stay longer in the training process.

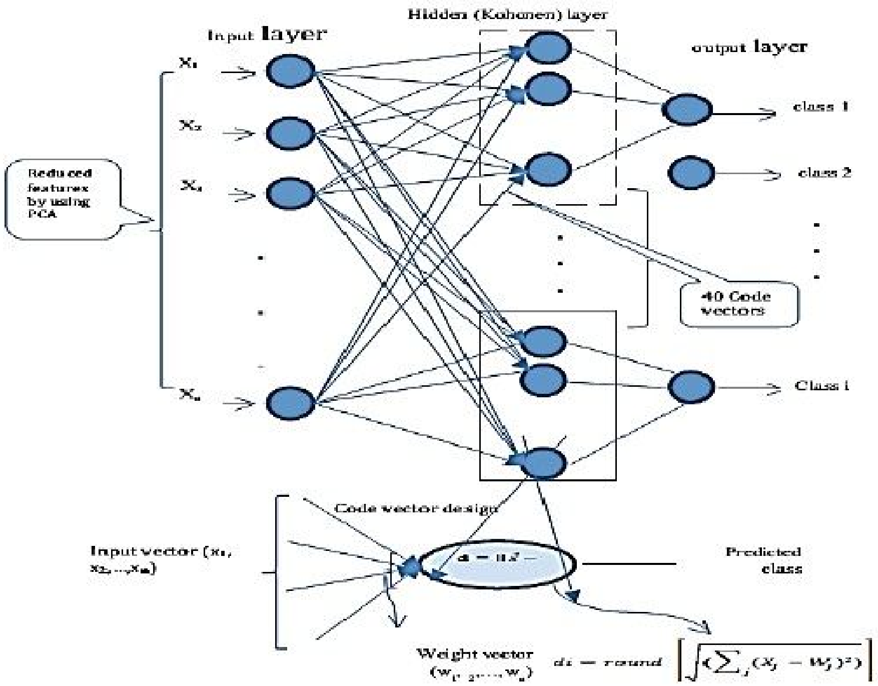

Figure 2 LVQ Neural Network classifier [10]

THE EXPERIMENT DATASETS

To perform a reliable evaluation for rounding off Euclidean distance function, four datasets are used. These sets are the collected MRI brain images, segmented challenge, image segmentation and segmented test. These sets are downloaded from UCI Machine learning Repository Web. Samples of from the collected images and the resulted images of the preprocessing step are shown in Fig. 3 and Fig 4

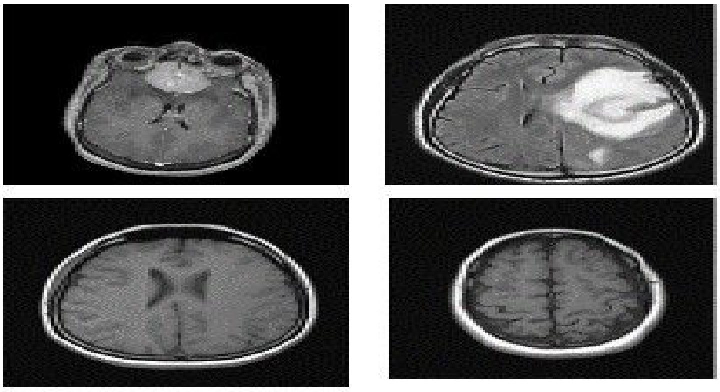

Figure 3 (row1) abnormal MRI images type t1-axial weighted (row2) normal MRI images type t2 –axial weighted

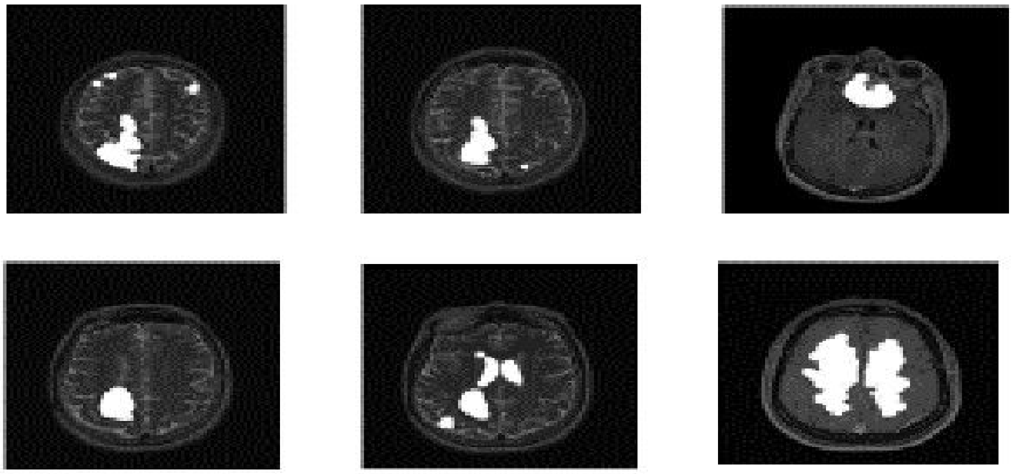

Figure 4 sample pictures of the image preprocessing step output

THE INITIAL SETTING THE CLASSIFIERS

Table 1 represents all the different parameters used with LVQ classifiers and these parameters are chosen by experiment.

Table 1: intial status of LVQ classifiers

parameter	Initial status
Learning rate	0.3
No. of iterations	2000
No. of codebook vectors	40
Evaluation Method	The average of Split percentages 50,55,60,65,67,70,75

Table 2: The average accuracy rates with and without rounding off the Euclidean distance function

DATA	LVQ1		Multi P LVQ		High LVQ		ptimised LVQ3	
	Before Round	After ound	Before Round	After ound	Before ound	After ound	Before ound	After ound
Brain images data (PPUKM)	80	76	79	70	79	74	75	76
Segmented challenge (UCI)	89	77	91	64	93	74	88	73.9
Segment test (UCI)	85	77	89	68	90	70	86	62.5
Average accuracy	7%	6.67%	6.33%	7.33%	7.33%	72.67%	3.00 %	70.80%
Std	.51	.58	6.43	3.06	7.37	2.31	7.00	7.26

Table 2 shows the average accuracy performance of the LVQ family classifiers. It is very clear that the average accuracy rates of the classifiers did not show any improvement, in fact it decreased. In the contrary the standard deviation (STD) values improved significantly with the proposed method. This improvement can be interpreted as better stability for the classifiers performance. The best Std values is 0.58 obtained by LVQ1. OLVQ3 classifier did not show any improvement either for the accuracy performance rate nor the STD value. Multi Pass LVQ and Hierarchy LVQ (HLVQ) also showed better stability with the proposed methode in which they obtained 2.3 and 3.06 STD values as presented in Fig. 5.

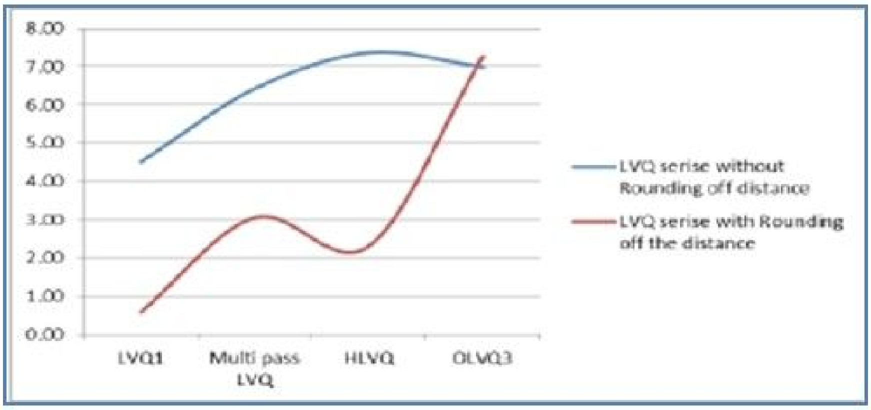

Figure 5 **The Standard deviation improvement**

DISCUSSION

This paper evaluated the performance of four LVQ classifiers with the proposed method. The results showed poor accuracy rates with applying the proposed method. However, the stability of the LVQ classifiers (LVQ1, multipass LVQ, HLVQ, OLVQ3) showed significant improvement in terms of the standard deviation values. The results showed a significant differences between the stability of these classifiers. The LVQ1 outperformed the other classifiers.The future work will concentrate on finding new methods to improve the accuracy rate of the LVQ classifiers as well as the stability. In addition the accuracy rate of LVQ's with the brain data set (2 classes) were stable unlike the other two data sets (7 classes) due to the close distance between the different classes which increases the incorrect classification with applying rounding off the Euclidean distance function method .

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