International Journal of Recent Engineering Research and Development (IJRERD)
ISSN: 2455-8761
www.ijrerd.com || Volume 02 – Issue 09 || September 2017 || PP. 47-52

An MR Brain Images Classifier using LGD Fitting Energy via Principal Component Analysis and Kernel Support Vector Machine

Shagun Sharma[1], Rakesh Kumar[2], Mukesh Kumar Saini[3]
[1]*Research Scholar, Sobhasaria Group of Institutions, Department of ECE, Sikar*
[2]*Asistant Professor, Sobhasaria Group of Institutions, Department of ECE, Sikar*
[3]*Assistant Professor, Sobhasaria Group of Institutions, Department of ECE, Sikar*

Abstract: In medical image processing extremely important for medical analysis and interpretation for Brain tumor segmentation from MRI scan slice without human intervention has become one of the most challenging area in research.MR image slices usually contain a significant amount of noise caused by operator interactions, environmental or external factors, machines used etc, which in turn may cause serious segmentation inaccuracy. Our main aim is to recognize a tumor and its quantification from a specific MRI scan of a brain image to obtain the best segmentation in minimum time. Over the last decade numerous methods have already been proposed. In this paper, we develop a novel method to classify a given MR brain image as normal or abnormal and tumor region is extracted from the MR images and its exact position and shape is determined with minimum time. The proposed method First employed wavelet transform to extract features from images, followed by applying principle component analysis (PCA) to reduce the dimensions of features. The reduced features were submitted to a kernel support vector machine (KSVM). The strategy of K-fold stratified cross validation was used to enhance generalization of KSVM. The Experimental results clearly define the effectiveness of our approach in its accuracy and computation time.

Keywords: Image processing, PCA, KSVM, MRI, SVM, LGDF and DWT etc.

1. Introduction

Magnetic resonance image provide easy identification of the abnormal region in brain. MR image is the most widely and effectively use medical imaging technique in the diagnostic of various cancerous diseases. For a completely automated system MRI plays an important role than any other imaging system. Magnetic resonance imaging (MRI) produces high quality images of the anatomical structures of the human body, especially in the brain, and provides rich information for clinical diagnosis and biomedical research. The diagnostic values of MRI are greatly magnified by the automated and accurate classification of the MRI images. Wavelet transform is an effective tool for feature extraction from MR brain images, because it allows analysis of images at various levels of resolution due to its multi-resolution analytic property. However, this technique requires large storage and is computationally expensive [9]. In order to reduce the feature vector dimensions and increase the discriminative power, the principal component analysis (PCA) was used [10]. PCA is appealing since it effectively reduces the dimensionality of the data and therefore reduces the computational cost of analyzing new data [11]. Then, the problem of how to classify on the input data arises. In recent years, researchers have proposed a lot of approaches for this goal, which fall into two categories. One category is supervised classification, including support vector machine (SVM) [12] and k- nearest neighbors (k-NN) [13]. The other category is unsupervised classification [14], including self-organization feature map (SOFM) [12] and fuzzy c-means [15]. While all these methods achieved good results, and yet the supervised classifier performs better than unsupervised classifier in terms of classification accuracy (success classification rate). However, the classification accuracies of most existing methods were lower than 95%, so the goal of this paper is to find a more accurate method.

The local image intensities are described by Gaussian distributions with different means and variances .By using a kernel function; we first define a local energy to characterize the fitting of the local Gaussian distribution to the local image data around a neighborhood of a point. The local energy is then integrated over the entire image domain to form a double integral energy: local Gaussian distribution fitting (LGDF) energy. The local intensity means and variances, which are spatially varying functions, are two variables of the LGDF energy functional. The LGDF energy is then incorporated into a variation level set formulation with a level set regularization term. In the resulting curve evolution that minimizes the associated energy functional, the local intensity in formation issued to compute the means and variances and thus guide the motion of the contour toward the object boundaries. Therefore, it can be used to segment images in the presence of intensity in homogeneity and noise. First, the LGDF energy is defined as a double integral: the first integral is defined with a kernel function to characterize the fitting of the local Gaussian distribution to the local image data around a neighborhood of a point; this local energy is then integrated to form the data term as a double integral in our variation formulation. Second, the local intensity means and variances, which are two variables of the proposed energy functional, are strictly derived from a variation principle, instead of being defined empirically.

2. Related Works and Processing

Brain tumors, can't be simply classified based on intensity variation or their existing size, which may be due to overlapping intensities with normal tissue. In Medical image processing, segmentation is considered as one of the hottest research topic. Researchers have suggested various methodologies and algorithms for successful segmentation of images. There are many existing approaches for the successful segmentation of brain image, such an automatic and semi-automatic method. In practical, manual segmentation is very difficult and tedious process, it require human interaction and in some cases it fails to produce accurate result, hence automated brain tumor segmentation method is most preferred now a days. In total, our method Implementation steps are described as follows,

Step-1 Preprocessing (including feature extraction and feature reduction);
Step-2 Training the kernel SVM;
Step-3 Conduct the connectivity processing to eliminate small false target area caused by noise.
Step-4 Make the coarse segmentation of clustering as the initial contour of LGDF model, which is the initial value of the level set function in the LGDF model.
Step 5 Conduct the evolution of the level set function, i.e. updating the local means and local variances.
Step-6 Judge whether the level set function convergences or not; if not, return to Step4 till the end.
Step-7 Submit new MRI brains to the trained kernel SVM and output the prediction;

A canonical and standard classification method, which has already been proven as the best classification method, we will explain the detailed procedures of the preprocessing in the following subsections. We further implement the morphological image processing, which includes the connectivity processing [8]. In the 2-D binary image segmentation result of K-means clustering on the original image, 8-connected components are computed, and every object is assigned different labels. Then we can get the target area in the segmentation. By this process, small false target area caused by noise could be eliminated.

3. LGDF Model

The LGDF model is put forward by [7] to take full advantage of local information of the image. In LGDF, the local image intensities are described by Gaussian distributions with different means and variances. The data fitting energy function is defined as follows,

$$Ex^{LGDF} = \sum_{i=1}^{2} \int_{\Omega} -\rho\,(x-y)\,log\,p_{1,x}\,(I(y))dy \qquad (1)$$

In the formula, ***-ρ(x-y)*** is a non-negative weighting function chosen as a truncated Gaussian kernel with a localization property. $\boldsymbol{p_{t,x}(I(\ y))}$ is the probability density function of the number i district, which follows the following Gaussian distribution,

$$p_{t,x}\big(I(y)\big) = \frac{1}{\sqrt{2\pi\sigma_t(x)}}\exp\left(-\frac{(u_t(x)-I(y))^2}{2\sigma_t{}^2(x)}\right) \qquad (2)$$

The length term could maintain smoothness of the evolution curve and avoid small isolated area in the final segmentation result. The energy punishment term could correct the deviation between the level set function and signed distance function in real time, which could avoid complex, time-consuming re-initialization and could ensure the stability of numerical calculation. The length term is given by

$$\mathcal{L}(\emptyset) = \int_{\Omega} \delta\big(\emptyset(X)\big)|\nabla\,\emptyset(X)|dx \qquad (3)$$

The energy punishment terms is given by the following integral

$$\rho(\emptyset) = \int_{\Omega} \frac{1}{2}\ \ (|\nabla\emptyset(X) - 1|)^2 dx \qquad (4)$$

then the final whole energy function is as following

$$f(\emptyset, u, \sigma^2) = \sum_{i=1}^{2}\ \ \int_{\Omega_i} -\rho\ (x-y)\log p_{i,x}\,(I(y)dy + a\mathcal{L}(\emptyset) + bp(\emptyset) \qquad (5)$$

where a and b are non-negative constants.

4. Feature Extraction

The most conventional tool of signal analysis is Fourier transform (FT), which breaks down a time domain signal into constituent sinusoids of different frequencies, thus, transforming the signal from time domain to frequency domain. However, FT has a serious drawback as discarding the time information of the signal. For example, analyst cannot tell when a particular event took place from a Fourier spectrum. Thus, the quality of the classification decreases as time information is lost.

Another advantage of WT is that it adopts “scale" instead of traditional “frequency", namely, it does not produce a time-frequency view but a time-scale view of the signal. The time-scale view is a different way to view data, but it is a more natural and powerful way, because compared to “frequency", “scale" is commonly used in daily life. Meanwhile, “in large/small scale" is easily understood than “in high/low frequency". Wavelet transform (WT) represents the next logical step: a windowing technique with variable size. Thus, it preserves both time and frequency information of the signal.

5. K-SVM

The introduction some prescribed data points each belong to one of two classes and the goal is to classify which class a new data point will be located in a landmark in the field of machine learning. The advantages of SVMs include high accuracy, elegant mathematical tractability, and direct geometric interpretation [19]. Recently, multiple improved SVMs have grown rapidly, among which the kernel SVMs are the most popular and effective. Kernel SVMs have the following advantages: (1) work very well in practice and have been remarkably successful in such diverse fields as natural language categorization, bioinformatics and computer vision; (2) have few tunable parameters; and (3) training often involves convex quadratic optimization. Hence, solutions are global and usually unique, thus avoiding the convergence to local minima exhibited by other statistical learning systems, such as neural networks. Here a data point is viewed as a *p*-dimensional vector, and our task is to create a (*p*-1) dimensional hyper plane. There are many possible hyper planes that might classify the data successfully. One reasonable choice as the best hyper plane is the one that represents the largest separation, or margin, between the two classes, since we could expect better behavior in response to unseen data during training, i.e., better generalization performance. Therefore, we choose the hyper plane so that the distance from it to the nearest data point on each side is maximized [12]. Figure 1 shows the geometric interpolation of linear SVMs, here H1, H2, H3 are three hyper planes which can classify the two classes successfully, however, H2 and H3 does not have the largest margin, so they will not perform well to new test data. The H1 has the maximum margin to the support vectors (*S*11, *S*12, *S*13, *S*21, *S*22, and *S*23), so it is chosen as the best classification hyper plane. a p-dimensional N-size training dataset of the form.

$$\{(x_n, y_n) | x_n \in R^p, y_n \in \{-1, +1\}\} \qquad n = 1, \dots\dots, N \tag{6}$$

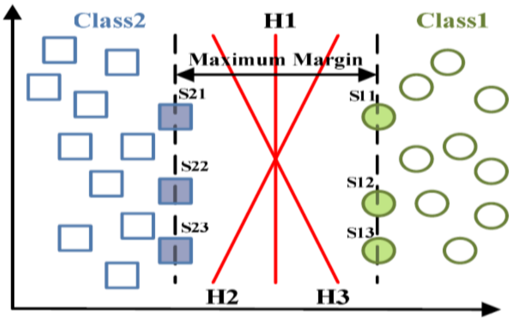

Figure 1: Linear SVMs

Traditional SMVs constructed a hyper plane to classify data, so they cannot deal with classification problem of which the different types of data located at different sides of a hyper surface; the kernel strategy is applied to SVMs [17]. The resulting algorithm is formally similar, except that every dot product is replaced by a nonlinear kernel function. In another point of view, the KSVMs allow to the maximum-margin hyper plane in a transformed feature space. The transformation may be nonlinear and the transformed space higher dimensional; thus though the classifier is a hyper plane in the higher-dimensional feature space, it may be nonlinear in the original input space. Three common kernels [18]. For each kernel, there should be at least one adjusting parameter so as to make the kernel flexible and tailor itself to practical data.

6. Experiments and Discussions

The experiments were carried out on the platform of P4 IBM with 3 GHz processor and 2GB RAM, running under Windows XP operating system. The algorithm was in-house developed via the wavelet toolbox, the bio-statistical toolbox of MATLAB 2010a (The Mathworks c°). We downloaded the open SVM toolbox, extended it to Kernel SVM, and applied it to the MR brain images classification. The programs can be run or tested on any computer platforms where MATLAB is available. The pre-segmentation by K-means clustering and the result by connectivity processing are shown in Figure 2. It shows that the clustering contour is in accordance with visual target contour. Then this result is set as the initial contour of the LGDF model. Since the initial contour is similar to the real target contour, the algorithm overcomes the bad effects of LGDF segmentation model by manually selecting initial contour. Besides, it reduces the number of iterations of the level set function to a certain extent. However, the evolution of the level set function takes much time. The second and third columns manifest the result of other initial contour position. It clearly demonstrates that the result is affected by the choice of the initial contour. From these three columns of Figure 3, we could conclude that a suitable initial contour can lead to a quality result, but an unsuitable one will affect the result and even bring about the failure of the segmentation. In the last column, the segmentation from the initial contour by K-means clustering processing is very ideal. Besides, iteration of the level set is cut down and the calculation process is reduced in comparison with the previous three results.

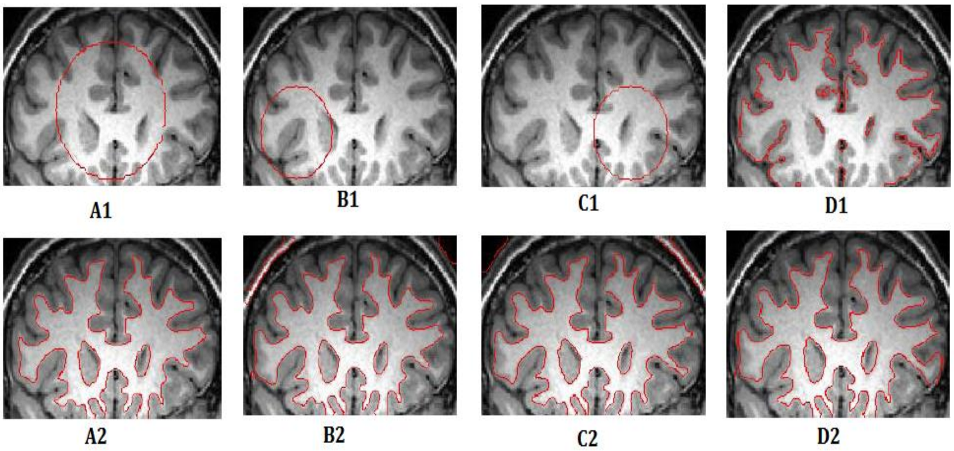

Figure 2: The segmentation results of brain image.

We randomly selected 20 images for each type of brain. Since there are one type of normal brain and seven types of abnormal brain in the dataset, 160 images are selected consisting of 20 normal and 140 (= 7 types of diseases 20 images/diseases) abnormal brain images.

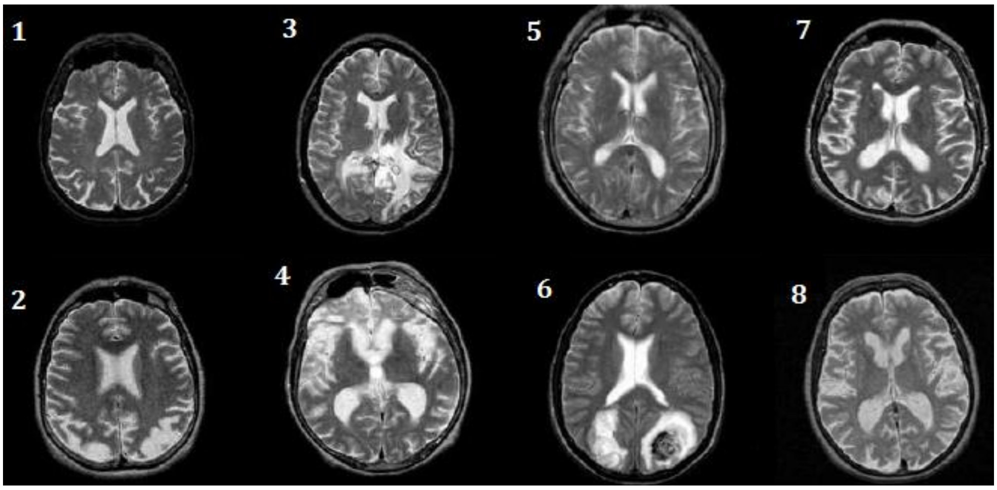

Figure 3: Brain MRI Samples: (1) Normal Brain (2)Alzheimer's Disease (3) Glioma (4) Pick's Disease (5) Meningioma (6) Sarcoma (7) Alzheimer's Disease (8) Huntington's Disease

Table 1: Comparison of segmentation results of Figure 3

Parameters	*Classification Accuracy (%)*
DWT+PCA+ACPSO+FNN	98.75%
DWT+PCA+KSVM (GRB)	99.38%
DWT+PCA+KSVM (GRB)+ LGD Fitting Energy Model	99.61%

The feature extraction stage is the most time-consuming as 0.023 s. The feature reduction costs 0.0187 s. The SVM classification with Local Gaussian Distribution Fitting Energy Model costs the least time only 0.0009 s. It indicates that our proposed method DWT+PCA+KSVM (GRB) + LGD Fitting Energy Model performed best methods, achieving the best classification accuracy as 99.61%. The next is DWT+PCA+ACPSO+FNN method with 98.75% classification accuracy. The second is our proposed DWT+PCA+KSVM (GRB) with 99.38% classification accuracy.

7. Conclusion

MRI images are best suitable for brain tumor detection. In this study Digital Image Processing Techniques are Important for brain tumor detection by MRI images. The preprocessing techniques include different methods like Filtering, Contrast enhancement, Edge detection is used for image smoothing. The preprocessed images are used for post processing operations like; threshold, histogram, segmentation and morphological, which is used to enhance the images. In this study, we have developed a novel DWT+PCA+KSVM method to distinguish between normal and abnormal MRIs of the brain. We picked up four different kernels as LIN, HPOL, IPOL and GRB. The experiments demonstrate that the GRB kernel SVM obtained 99.38% classification accuracy on the 160 MR images, higher than HPOL, IPOL and GRB kernels, and other popular methods in recent literatures. The proposed DWT+PCA+KSVM with GRB kernel method show superiority to the LIN, HPOL, and IPOL kernels SVMs. The reason is the GRB kernel takes the form of exponential function, which can enlarge the distance between samples to the extent that HPOL can't reach. Therefore, we will apply the GRB kernel to other industrial fields.

References

[1] Zhang, Y., L. Wu, and S. Wang, "Magnetic resonance brain image classification by an improved artificial bee colony algorithm," Progress In Electromagnetic Research, Vol. 116, 65-79, 2011.

[2] Mohsin, S. A., N. M. Sheikh, and U. Saeed, "MRI induced heating of deep brain stimulation leads: Effect of the air-tissue interface," Progress In Electromagnetic Research, Vol. 83, 81-91, 2008.

[3] Chaplot, S., L. M. Patnaik, and N. R. Jagannathan, "Classification of magnetic resonance brain images using wavelets as input to support vector machine and neural network," Biomedical Signal Processing and Control, Vol. 1, No. 1, 86-92, 2006.

[4] Zhang, Y., S. Wang, and L. Wu, ''A novel method for magnetic resonance brain image classification based on adaptive chaotic PSO," Progress In Electromagnetic Research, Vol. 109, 325-343, 2010.

[5] Kass M, Witkin A, et al. Snakes, ''Active contour models,'' International Journal Computer Vision. 1988; 1(4):322–31.

[6] Warfield S, et al, ''Automatic identification of gray matter structures from MRI to improve the segmentation of white matter lesions,'' International Journal of Computer Vision. 1996.

[7] Rohit M, Kabade S, Gaikwad MS,''Segmentation of brain tumour and its area calculation in brain MRI images using K-mean clustering and Fuzzy C-mean algorithm. Int J Computer science Engineering Technology (IJCSET). 2013; 4(5):524–31.

[8] Kimmel R, Amir A, Bruckstein A,'' Finding shortest paths on surfaces using level set propagation,'' IEEE Trans Pattern Anal Mach Intell. 1995; 17(6):635–40.

[9] R. Kimmel, A. Amir, A. Bruck stein, ''Findings hortest pathson surfaces using level set propagation, IEEE Trans. Pattern Anal. Mach. Intell. 17(6)(1995)635–640.

[10] C. Li, C. Kao, J.C. Gore, Z. Ding, ''Minimization region –scalable fitting energy for image segmentation, ''IEEE Trans. Image Process.17 (10)(2008)1940–1949.

[11] Amer Al-Badarnech, Hassan Najadat, Ali M. Alraziqi, "A Classifier to Detect Tumor Disease in MRI Brain Images", IEEE Computer Society, ASONAM. 2012,142

[12] Usha Mittal, Sanyam Anand, "Modified Watershed Segmentation with Denoising of Medical Images," IJIRSET, Vol. 2, Issue 4, April 2013.
[13] Ashraf A. Aly, Safaai Bin Deris, Nazar Zaki, "Research review for digital image Segmentation stechniques", IJCSIT, Vol 3, No 5, Oct 2011
[14] Mohammed Y. Kamil, "Brain Tumor Area Calculation in CT-scan image using Morphological Operations", IOSR Journal of Computer Engineering (IOSR-JCE) ISSN: 2278-8727, Volume 17, Issue 2,Ver.-V, PP 125-128, Mar – Apr. 2015.
[15] Poonam, Jyotika Pruthi, "Review of image processing techniques for automatic detection of tumor in human brain", IJCSMC, Vol.2, Issue.11, November 2013, pg.117-122.
[16] Rajesh C. patil, A.S. Bhalchandra, "Brain tumor extraction from MRI images Using MAT Lab", IJECSCSE, ISSN: 2277-9477, Volume 2, issue1.
[17] Vinay Parmeshwarappa, Nandish S, "A segmented morphological approach to detect tumor in brain images", IJARCSSE, ISSN: 2277 128X , volume 4, issue 1, January 2014.
[18] Kashyap, R. & Gautam, P. ''Microarray Image Segmentation Using Improved GOGAC Method,'' International Journal Of Computer Science And Engineering, (2013). 2(4), 67-74.
[19] Prasad, V. & Gopal, R,''LHM Filter for Removal Salt and Pepper with Random Noise in Images,'' International Journal Of Computer Applications, 139(1), 9-15. (2016).
[20] Patil, N. S., et al., ''Regression models using pattern search assisted least square support vector machines," Chemical Engineering Research and Design, Vol. 83, No. 8, 1030{1037, 2005.

Shagun Sharma received the B.Tech. degree (Electronics & Communication) from Manav Institute of Technology and Management, Hisar, Hariyana in 2012 now Pursuing M.Tech. (Digital Communication) from Sobhasaria Engineering College.

Rakesh Kumar received the B.E. degree (Electronics & Communication) from Shekhawati Engineering College, Dundlod (Raj.) in 2007. and M.Tech. degree (VLSI Design) from C-DAC Mohali in 2009. He now with Sobhasaria Engineering College, Sikar, as Assistant Professor in department of electronics and Communication.

Mukesh Kumar Saini received the B.E. degree (Electronics & Communication) from Sobhasaria Engineering College, Sikar (Raj.) in 2008. and M.Tech. degree (Digital Communication) from Govt. Engineering College, Ajmer in 2015. He now with Sobhasaria Engineering College, Sikar, as Assistant Professor in department of electronics and Communication.