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A short contemporary survey on pathological brain detection

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Abstract. Brain disease detection still is the hotspot and difficulty in the present society. Nevertheless, the emergence of magnetic resonance imaging (MRI) technology can be more convenient for the diagnosis of brain diseases. In this paper, we introduce several methods to detect pathological brain automatically, and analyze their advantages and disadvantages as well as to the direction of the future.

Introduction

Developing a pathological brain detection system (PBDS) is the tendency of social progress. With the comparison to the traditional method, it can help doctors to detect disease for patients accurately [1, 2]. Meanwhile, the patient can quickly get the pathological findings so as to get treatment.

Magnetic resonance imaging (MRI) [3-6] is a type of tomography. Its mechanism is based on magnetic resonance phenomena. Using MRI, the scanner can attain EM (full name is electromagnetic) signals [7-9]. Afterwards, the algorithm can reconstruct the inner image among human structure. It is suitable for almost diseases of the system, such as cancer, inflammation and a variety of congenital diseases [10-15]. The most important thing is that it does not contain any radiations [16-18].

In this paper, we will introduce some approaches for detecting pathologic brain disease and analyze the advantages and disadvantages.

Methods and Results

Lu (2016) [19] proposed a radial basis function neural network (RBFNN) to classify the brain images, Meanwhile, they compared its method with following five methods: (i) BPNN; (ii) DWT+PCA+SVM; (iii) WE+NBC; (iv) RT+PCA+LS-SVM; (v) RBFNN. The results showed that the accuracy of WE+RBFNN is higher than other methods.

Yang (2016) [20] proposed wavelet-energy to reduce the dimension of features. Then, they used the support vector machine (SVM) as classifier, meanwhile, this paper employed the biogeography-based optimization (BBO) to find the most suitable parameters, i.e., σ and C. Further, the accuracy, sensitivity, specificity and precision of this method achieved 97.78%, 98.12%, 92%, and 99.52%, respectively.

Zhang (2016) [21] employed 2-level stationary wavelet entropy (SWE) to extract feature, then they compared three methods: (i) the decision tree, (ii) *k*-nearest neighbors (shorted as KNN), (iii) support vector machine (abbreviated as SVM). The authors found that KNN performed the best among three classifiers. Therefore, they proposed “SWE + KNN” to detect multiple sclerosis (MS).

Zhou (2016) [22] proposed “WE+FNN” to classify a MR brains image as normal or abnormal. They made tests based on 1-5 decomposition levels to find which leads to the highest accuracy, the results showed that first-level decomposition achieves 100% accuracy and its only contains four

features. However, this experiment used 64 images which it is very small.

Wang (2016) [23] designed a novel approach via an effective feature—fractional Fourier transform (FRFT) and a traditional feature reduction method—principal component analysis (PCA) to detect unilateral hearing loss. This paper employed a single-hidden-layer feed-forward neural network (SFNN) as classifier and used the classical Levenberg-Marquardt algorithm to train SFNN.

Wang (2016) [24] selected 28 Alzheimer's disease (AD) and 98 healthy controls (HCs) from OASIS dataset in order to develop an AD detection system. This system included wavelet entropy, multilayer perceptron (MLP) and biogeography-base optimization (BBO). Thereinto, the BBO was used to train MLP, in addition, experiments showed that BBO performed better than other swarm intelligence based training algorithms.

Chen (2016) [25] proposed "DWT+PCA+GEPSVM (with Tikhonov regularization)" to detect sensorineural hearing loss (SNHL). Experiment showed that the total accuracy achieved 95.71% when the threshold in PCA was set to 99%.

Sun (2016) [26] employed two-dimensional (2D) discrete wavelet transform (DWT). Their chose Haar wavelet. The authors used a three-level decomposition. Finally, the obtained 10 subbands.

In the classification stage, they employed the support vector machine with different kernels (KSVM). They tested the performances of different kernels. A new algorithm: quantum-behaved particle swarm optimization (abbreviated as QPSO) was used to train KSVM. In the experiment, their simulation showed that the accuracy achieved 98.22%, the precision achieved 99.52%, the specificity was 92.00%, and the sensitivity was 98.59%.

Yang (2016) [27] proposed a dual-tree DWT in order to improve the directional selectivity impaired by DWT. For an m-level decomposition, they extracted $12m$ variance and entropy (VAE) features based on the coefficients of DTCWT. Further, this paper used SVM, generalized Eigenvalue Proximal SVM (GEPSVM), twin SVM (TSVM) as classifier. The results of experiment show that "DTCWT-VAE-TSVM" was superior to "DTCWT-VAE-SVM/GEPSVM" and other 19 contemporary methods. However, this approach also had limitations: the size of dataset was too small.

Zhang (2016) [28] put forward fractional Fourier entropy (FRFE) and multi-layer perceptron (MLP) in order to develop a novel pathological brain detection system (PBDS). This paper proposed two improvements including pruning technique (PT) and Biogeography-based optimization (BBO). Meanwhile, this paper introduced and made comparison among 3 pruning methods: (1) Kappa coefficient (KC); (2) dynamic pruning (DP); and (3) Bayesian detection boundaries (BDB).

Siddiqui (2015) [29] tested more than 300 subjects. The scans are of both T1-weighted and T2-weighted. Further, its method improved the efficiency of feature extraction significantly by more than 70 percentage. Their method improved dimension reduction and classification slight by less than 5 percentage.

Discussion and conclusion

In this paper, we introduce several methods to classify a brain image as abnormal or normal. Furthermore, we summarized the characteristics of these methods in **Table 1**. In the future, we shall discuss smart detection on other parts (not brain), such as breast [30, 31], lung, etc.

Table 1 Comparison of several classification algorithms

Author	Method used	Limitation	Accuracy
Lu (2016) [19]	2D discrete wavelet transform (DWT) was used to extract features, wavelet-entropy (WE) to reduce the dimension of features, RBFNN	The dataset only contains 125 images.	95.44%
Yang (2016) [20]	WE-SVM-BBO	The brain dataset contains 90 images which is too small.	97.78%
Zhang (2016) [21]	SWE, KNN, 10-fold cross validation to prevent over-fitting.	KNN needed to calculate the distance k times in the validation stage.	97.94%
Zhou (2016) [22]	2-level 2D DWT, Wavelet entropy (WE), FNN as classifier.	The dataset only obtains 64 images.	100%
Wang (2016) [23]	fractional Fourier transform (FRFT), PCA, SFNN	This experiment only contains 49 subjects.	95.1%
Wang (2016) [24]	WE, multilayer perceptron, biogeography-base optimization	Wavelet-entropy is low efficiency compared with other methods, such as scale	92.40%
Chen (2016) [25]	DWT was applied to decompose brain images and used the PCA to reduce the dimension of features.	The sensitivity of this method is lower than "WPD+LS-SVM" in S_2 and S_3	95.71%
Sun (2016) [26]	DWT-KSVM-QPSO	one Lyme Encephalopathy image was wrongly classified as normal	98.22%
Yang (2016) [27]	proposed and compared three different classifiers based on DTCWT-VAE	the dataset does not reflect the actual situation	99.57%
Zhang (2016) [28]	fractional Fourier entropy (FRFE) to extract 12 features for each brain image, multi-layer perceptron (MLP)	This approach was only applied to T2-weighted images.	99.53%
Siddiqui (2015) [29]	DWT, PCA, LS-SVM with radial basis function (RBF), *k*-fold stratified cross validation	This approach can only verified brain MRIs.	100%

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