Neurocomputing 177 (2016) 188–197

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Brain MR image classification using two-dimensional discrete wavelet transform and AdaBoost with random forests

Deepak Ranjan Nayak*, Ratnakar Dash, Banshidhar Majhi

Pattern Recgnition Research Lab, Department of Computer Science and Engineering, National Institute of Technology, Rourkela 769 008, India

ARTICLE INFO

Article history:
Received 1 September 2015
Received in revised form
7 November 2015
Accepted 19 November 2015
Communicated by Yongdong Zhang
Available online 2 December 2015

Keywords:
Magnetic resonance imaging (MRI)
Discrete wavelet transform (DWT)
Probabilistic principal component analysis (PPCA)
AdaBoost with random forests (ADBRF)
Computer-aided diagnosis (CAD)

ABSTRACT

This paper presents an automated and accurate computer-aided diagnosis (CAD) system for brain magnetic resonance (MR) image classification. The system first utilizes two-dimensional discrete wavelet transform (2D DWT) for extracting features from the images. After feature vector normalization, probabilistic principal component analysis (PPCA) is employed to reduce the dimensionality of the feature vector. The reduced features are applied to the classifier to categorize MR images into normal and abnormal. This scheme uses an AdaBoost algorithm with random forests as its base classifier. Three benchmark MR image datasets, Dataset-66, Dataset-160, and Dataset-255, have been used to validate the proposed system. A 5×5-fold stratified cross validation scheme is used to enhance the generalization capability of the proposed scheme. Simulation results are compared with the existing schemes and it is observed that the proposed scheme outperforms others in all the three datasets.

1. Introduction

Magnetic resonance imaging (MRI) is a low risk, fast, non-invasive imaging technique that has become a powerful tool for studying the human brain. MRI utilizes magnetic fields and radio waves to produce high-quality images of the anatomical structures of the brain without the use of ionizing radiation (X-rays) or radioactive traces. It gives enormous information about the soft brain tissues which is useful for clinical diagnosis and biomedical research [1]. Compared to all other imaging techniques, MRI provides superior contrast for different brain tissues and generates fewer artifacts [2–4]. These properties have characterized MRI as the most popular tool for brain pathology diagnosis and treatment. However, high volume of imaging data leads difficulty to an observer in analyzing and interpreting brain images manually. Besides, existing manual methods of detecting diseased brain are tedious, time-consuming, costly, and subject to the weariness of observers. Hence, there is a demand for developing automated and accurate computer-aided diagnosis (CAD) systems to draw faster and easier inferences from MR images. These systems can be of great importance to facilitate the medical personnel in the diagnosis, prognosis, pre-surgical and post-surgical processes, etc. [3,5]. The most identifiable feature of a human brain is the symmetry which is apparent in the axial and coronal brain magnetic resonance (MR) images. In contrast, asymmetry in the axial images strongly designates the abnormality or disease. So, these essential features can be modeled by different signal and image processing techniques in order to classify the normal and abnormal brain MR images [3].

In recent years, various techniques for brain MR image classification have been suggested by different researchers. In [3], the coefficients of the level-3 approximation sub-band of two-dimensional discrete wavelet transform (2D DWT) are utilized for feature extraction, where Daubechies 4 (DAUB-4) filters are used as the decomposition filters. They have achieved 94% and 98% accuracy through the classifiers based on self-organizing map (SOM) and support vector machine (SVM), respectively. Maitra and Chatterjee [4] have employed Slantlet transform (ST), an improved version of DWT for feature extraction from the intensity histogram of brain MR images. Then, they have used back-propagation neural network (BPNN) classifier to accomplish 100% success rate. El-Dahshan et al. [6] have utilized the coefficients of the approximation sub-band of 2D DWT as a feature vector for each brain MR image. Then, principal component analysis (PCA) was applied to the feature vector to reduce the number of coefficients. They have used feed forward back-propagation artificial neural network (FP-ANN) and k-nearest neighbor (k-NN) classifiers to categorize images as normal and abnormal and achieved 97% and 98% accuracy, respectively. Zhang et al. [2,7–10] have suggested several hybrid approaches for brain image classification and obtained high classification accuracies. In all the existing approaches, they have used the coefficients of third-level approximation sub-band of 2D

* Corresponding author.
E-mail address: depakranjannayak@gmail.com (D.R. Nayak).

http://dx.doi.org/10.1016/j.neucom.2015.11.034
0925-2312/

DWT for feature extraction followed by PCA for feature dimension reduction. But different classifiers with improved parameter optimization schemes like feed forward neural network (FNN) with adaptive chaotic particle swarm optimization (ACPSO) [7], FNN with scaled chaotic artificial bee algorithm (SCABC) [8], BPNN with scaled conjugate gradient (SCG) [2], kernel SVM (KSVM) with different kernels: linear (LIN), homogeneous polynomial (HPOL), inhomogeneous polynomial (IPOL) and Gaussian radial basis (GRB) [9] and KSVM with PSO [10], have been used for isolating the normal and abnormal MR images. Das et al. [5] proposed a new multiscale geometric analysis (MGA) tool called Ripplet transform (RT) to extract essential features from the brain MR images. PCA was employed for feature reduction, and least square SVM (LS-SVM) was used to classify the brain images. Their result shows that the proposed classifier achieves high classification accuracy even with larger datasets. Saritha et al. [11] have proposed a combined wavelet entropy (WE) based spider web plots (SWP) for feature extraction. They have calculated the entropy of the approximation components of DAUB-4 wavelet up to 8-levels. Probabilistic neural network (PNN) was considered for classification of brain MR images, and their results indicate that their method earns high success rate with smaller feature dimension on a small dataset. Kalbkhani et al. [12] have first computed the two-level 2D DWT for each MR image and then used generalized autoregressive conditional heteroscedasticity (GARCH) statistical model to extract the parameters from the coefficients of detail sub-bands. These extracted parameters were considered as the primary features. Subsequently, both PCA and linear discriminant analysis (LDA) have been employed to find the relevant features from the primary ones. k-NN and SVM were separately used as the classifiers, and the results show that their suggested scheme achieves high classification accuracy with less number of features. El-Dahshan et al. [13] employed the median filter for pre-processing, the feedback pulse coupled neural network (FPCNN) for image segmentation, 2D DWT for feature extraction, PCA for dimensionality reduction of wavelet coefficients and feed forward back propagation neural network to segregate input MR images as normal and abnormal. They have reached 99% classification accuracy on both training and testing images. Yang et al. [14] have calculated energy values of the wavelet components of level-3 decomposition for feature extraction. SVM was used as the classifier and biogeography-based optimization (BBO) technique was suggested to optimize the weights of the SVM. They have shown that their method is superior to BPNN, KSVM, and PSO-KSVM. Zhang et al. [15] employed the discrete wavelet packet transform (DWPT) instead of DWT and introduced two entropy based methods, namely, Shannon entropy (SE) and Tsallis entropy (TE), for feature extraction from the DWPT coefficients. Then, they have utilized a generalized eigenvalue proximal SVM (GEPSVM) classifier and obtained significant results over state-of-the-art methods. Wang et al. [16] have achieved promising results on three standard datasets using the features extracted from the stationary wavelet transform (SWT), which unlike DWT, preserves translation-invariant property [17,18]. To reduce such large number of SWT coefficients, PCA was applied. Subsequently, they have suggested three different hybrid optimization techniques using artificial bee colony (ABC) and PSO, viz., integrated algorithm based on ABC and PSO (IABAP), artificial bee colony with standard particle swarm optimization (ABC-SPSO) and hybridization of PSO and ABC (HPA), to improve the performance of traditional FNN classifier. They have reported that their schemes are superior to other existing schemes. Zhang et al. [19] have presented 6-level DAUB-4 DWT decomposition and calculated the entropy value of the approximation components at each level. These entropy values were practiced as the features for the brain MR images. Then, they have proposed an optimization algorithm based on the hybridization of BBO and PSO (HBP) method to train the FNN classifier and obtained significant classification accuracy on three benchmark datasets.

From the literature review, it has been observed that most of the existing approaches use wavelet and its variations for feature extraction. For classification, both supervised and unsupervised schemes have been extensively utilized. However, most of the schemes have higher computational complexity and not suitable for real-time applications. Further, the reduced feature sets still are of higher dimension and have a scope to reduce it further. Even though the accuracies obtained are promising, they have used a smaller dataset and need to be exposed to a larger dataset.

Keeping this in mind, the prime motivation of this work is to develop an automated CAD system for brain MR image classification with less computational overhead and high classification accuracy in order to work efficiently with larger brain MR datasets. The scheme employs 2D DWT for feature extraction, probabilistic PCA (PPCA) for feature reduction, and AdaBoost with random forests (ADBRF) for classification of MR images into normal and abnormal. Extensive simulations on different datasets indicate that the proposed scheme earns better classification accuracies in comparison to other existing schemes. The generalization capability, computational efficiency, and high classification accuracy with only 13 discriminant features are the key advantages of the proposed scheme.

The remainder of this paper is organized as follows. Section 2 discusses the methodology of the proposed system. The experimental results and comparisons are presented in Section 3. Finally, Section 4 concludes the paper.

2. Proposed method

The proposed method consists of three important stages, namely, feature extraction using 2D DWT, feature dimensionality reduction using PPCA and classification using the AdaBoost algorithm with random forests (ADBRF). The overall block diagram of the proposed scheme is shown in Fig. 1. As shown, initially the approximation coefficients are extracted from MR images using level-3 2D DWT and stored in a primary feature matrix. The primary feature matrix has been normalized to have zero mean and unit variance prior to feature reduction stage. To derive reduced uncorrelated discriminant set of features, PPCA is utilized. Finally, the reduced features are classified by the ADBRF classifier. All three phases are discussed below in detail.

2.1. Feature extraction based on 2D DWT

The wavelet transform is a powerful mathematical tool for feature extraction of images and has become a popular choice in many image analysis and classification problems. This transform is useful to analyze the signal or image at different scales or resolutions [20]. Unlike other transformation techniques, wavelet transform provides time–frequency localization of a signal, which is extremely beneficial for classification [6].

Higher order wavelets are scaled and shifted versions of some fixed mother wavelets. Let $f(x)$ be a continuous, square-integrable function. The continuous wavelet transform of $f(x)$, relative to a real-valued wavelet, $\psi(x)$, is defined as,

$$W_\psi(s,t) = \int_{-\infty}^{+\infty} f(x)\psi_{s,t}(x)\,dx \tag{1}$$

where

$$\psi_{s,t}(x) = \frac{1}{\sqrt{s}}\psi\left(\frac{x-t}{s}\right); \quad s \in \Re^+, \ \ t \in \Re \tag{2}$$