Combining extreme learning machine with modified sine cosine algorithm for detection of pathological brain☆

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ARTICLE INFO

ABSTRACT

Development of automated diagnosis systems has taken a major place in current research practice to assist medical experts in decision-making. This paper presents a new automatic system for detection of pathological brain through magnetic resonance imaging (MRI). The proposed system involves contrast enhancement of input MR images using contrast limited adaptive histogram equalization (CLAHE). Then, the curve like features are computed from the preprocessed MR brain images using fast discrete curvelet transform via unequally-spaced FFT (FDCT-USFFT). Subsequently, a combined technique known as PCA + LDA is employed to derive more dis-criminative and reduced feature sets. Finally, a novel learning approach dubbed as extreme learning machine with modified sine cosine algorithm (MSCA-ELM) is proposed by combining ELM and MSCA for classification of MR images into two categories: pathological and healthy. A mutation operator is introduced to basic SCA (MSCA). In MSCA-ELM, MSCA is used to optimize the input weights and hidden biases of single-hidden layer feed-forward neural network (SLFN) and an analytical procedure is used to compute the output weights. The proposed scheme is rigorously evaluated on three standard datasets and the results are compared against other competent schemes. The experimental results demonstrate that the proposed scheme outperforms its counterparts in terms of classification accuracy and number of features required. It has also been noticed that MSCA-ELM yields superior performance than conventional learning methods. Hence, the proposed system can effectively recognize pathological brain in real-time and can possibly be installed on medical robots.

1. Introduction

Across the globe, the death rate of individuals with various age groups is increasing immeasurably due to several brain dis-eases [1]. Pathological brain detection (PBD) has played vital role for early diagnosis of various diseases such as Alzheimer's disease, mild cognitive impairment, autism spectrum disorder, multiple sclerosis, hearing loss, and microbleeding. The significant objective of PBD is to help radiologists in taking correct and quick clinical decisions. Magnetic resonance imaging (MRI), an advanced neuroi-maging technique, is frequently used in PBD because of its ability to provide better resolution of brain tissues and its radiation-free properties [2]. However, manual interpretation is tedious and may subject to error due to the high image contents [3,4]. Thus there is a strong demand for identification, evaluation and classification support tools in the diagnostic procedure. Pathological brain detection system (PBDS) development is a growing research area that aims at meeting these demands. Through PBDS we can speed up

the clinical decisions and reduce the diagnostic errors.

The work on PBD started in early 2000 [1,5]. The efforts then were initiated by Chaplot et al. [6] in which 2D discrete wavelet transform (2D DWT) and support vector machine (SVM) are used for feature extraction and classification. El-Dahshan et al. [7] have employed 2D DWT and two classifiers such as *k*-nearest neighbor (KNN) and feed forward back-propagation artificial neural network (FP-ANN). To reduce the feature dimensionality, they have applied principal component analysis (PCA). The authors in [2,8,9] have used scaled conjugate gradient (SCG), particle swarm optimization (PSO), adaptive chaotic PSO (ACPSO), and scaled chaotic artificial bee colony (SCABC) to train the feed forward neural network (FNN) classifier. Zhang et al. [10] have combined DWT, PCA and kernel SVM (KSVM). In [3], a ripplet transform (RT) and least squares SVM (LS-SVM) based system is suggested. In [11], the authors harnessed wavelet entropy (WE) to extract features and probabilistic neural network (PNN) is used for classification. Later, in [1], the authors have combined feedback pulse coupled neural network (FPCNN), DWT, PCA and FNN to detect pathological brain. Dong et al. [12] have utilized wavelet packet Shannon entropy (WPSE) and wavelet packet Tsallis entropy (WPTE) separately as features. In this, GEPSVM is employed as classifier. Nayak et al. [4] have utilized 2D DWT, probabilistic PCA (PPCA) and AdaBoost with random forests (ADBRF) for identifying pathological brains. Zhang et al. [13] have offered a PBDS which combines stationary wavelet transform (SWT), PCA, and GEPSVM. In [14], a PCA + LDA technique is applied on the 2D DWT features. In [15], Naive Bayes classifier (NBC) based PBDS is proposed which makes use of WE features. Sun et al. [16] have utilized GEPSVM + RBF classifier on WE and Hu moment invariants (HMI) features. Wang et al. [17] have proposed a novel feature called fractional Fourier entropy (FRFE) and performed Welch's *t*-test (WTT) to select the relevant features. Twin SVM (TSVM) classifier is employed for classification. Later, in [18], a PBDS based on FRFE features and multilayer perceptron (MLP) is proposed. They have employed an adaptive real coded BBO (ARCBBO) approach for training the MLP. In this case, the number of hidden neurons of MLP is found using three separate pruning methods, namely, Bayesian detection boundaries (BDB), dynamic pruning (DP) and Kappa coefficient (KC). Chen et al. [19] have utilized Minkowski-Bouligand dimension (MBD) features and proposed an improved PSO (IPSO) to train the single-hidden layer feedforward neural network. Later on, Wang et al. [20] combined the variance and entropy (VE) values of dual-tree complex wavelet transform (DTCWT) and TSVM to detect pathological brain. Li et al. [21] have employed wavelet packet Tsallis entropy (WPTE) and FNN with real-coded biogeography-based optimization (RCBBO) for pathological brain detection.

The literature studies reveals that 2D DWT and its variants (SWT, DTCWT, DWPT, etc.) are commonly used as the feature extractor. However, these transforms have limited capability of representing 2D singularities (edges and textures of an image). In other words, they can not capture curve like features from the images efficiently which is inherent in MRI scanning. Further, it has been noticed that most PBDSs employ classifiers such as FNN and SVM. However, traditional training algorithms for FNN such as Levenberg-Marquardt (LM) and back-propagation (BP), are slower and trapped at local minima. The computational complexity involved with standard SVM is very high. Furthermore, several PBDSs demand large number of features.

To resolve such issues, a novel framework for detection of pathological brain is proposed. The main contributions of this study are summarized as follows:

(a) Fast discrete curvelet transform via unequally-spaced FFT (FDCT-USFFT) is harnessed as feature extractor since it is efficient in capturing 2D singularities along with a group of curves.
(b) To combat the issues faced by conventional learning algorithms, a simple and non-iterative learning technique known as extreme learning machine (ELM) is employed.
(c) The concept of mutation is introduced to basic sine cosine algorithm (SCA) to enhance the global search capability and is referred to as modified sine cosine algorithm (MSCA).
(d) A novel learning algorithm known as MSCA-ELM is proposed based on MSCA and ELM to further enhance the performance of basic ELM.
(e) To evaluate the performance of the proposed scheme, extensive experiments are carried out on three well-known datasets. In this context, the performance of the suggested scheme is compared against its counterparts.

The remainder of this article is organized as follows. Section 2 offers the datasets used in this study. Section 3 discusses the details of the proposed methodology. In Section 4, the evaluation results on standard datasets and comparisons with existing schemes are presented. Finally, Section 5 concludes the work and suggests some possible future research directions.

2. Datasets used

The proposed PBDS has been evaluated on three benchmark datasets, namely, DS-I, DS-II, and DS-III which carries 66, 160 and 255 brain MR images respectively [3,4,12]. The datasets accommodate T2-weighted brain MR images of size 256×256 in axial view plane which were downloaded from Medical School of Harvard University website [22]. Both DS-I and DS-II hold samples of seven categories of diseases such as sarcoma, glioma, meningioma, AD plus visual agnosia (VA), Pick's disease (PD), AD and Huntington's disease (HD) plus healthy brain samples. However, DS-III includes four more diseases such as cerebral toxoplasmosis (CTP), multiple sclerosis (MS), herpes encephalitis (HE), and chronic subdural hematoma (CSH).

3. Proposed methodology

The proposed framework includes four vital components such as contrast limited adaptive histogram equalization (CLAHE) based preprocessing, FDCT-USFFT based feature extraction, PCA + LDA based feature dimensionality reduction, and MSCA-ELM based