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MAGNETIC RESONANCE BRAIN IMAGE CLASSIFICATION BY AN IMPROVED ARTIFICIAL BEE COLONY ALGORITHM

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Abstract—Automated and accurate classification of magnetic resonance (MR) brain images is a hot topic in the field of neuroimaging. Recently many different and innovative methods have been proposed to improve upon this technology. In this study, we presented a hybrid method based on forward neural network (FNN) to classify an MR brain image as normal or abnormal. The method first employed a discrete wavelet transform to extract features from images, and then applied the technique of principle component analysis (PCA) to reduce the size of the features. The reduced features were sent to an FNN, of which the parameters were optimized via an improved artificial bee colony (ABC) algorithm based on both fitness scaling and chaotic theory. We referred to the improved algorithm as scaled chaotic artificial bee colony (SCABC). Moreover, the K-fold stratified cross validation was employed to avoid overfitting. In the experiment, we applied the proposed method on the data set of T2-weighted MRI images consisting of 66 brain images (18 normal and 48 abnormal). The proposed SCABC was compared with traditional training methods such as BP, momentum BP, genetic algorithm, elite genetic algorithm with migration, simulated annealing, and ABC. Each algorithm was run 20 times to reduce randomness. The results show that our SCABC can obtain the least mean MSE and 100% classification accuracy.

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1. INTRODUCTION

Magnetic resonance imaging (MRI) is a noninvasive medical imaging technique used in radiology to visualize detailed internal structure and limited functions of the body [1]. It provides greater contrast between the different soft tissues of the body than computed tomography (CT) does, making it especially useful in neurological (brain), musculoskeletal, cardiovascular, and oncological (cancer) imaging [2, 3]. The diagnostic values of MRI are greatly magnified by the automated and accurate classification of the MR images [4, 5].

Wavelet transform is an effective tool for 2D image feature extraction because it allows for the analysis of images at various levels of resolution. However, it requires large storage and is computationally more expensive [6, 7]. In order to reduce the feature vector dimensions and increase the discriminative power, the principal component analysis (PCA) [8] method has been used. PCA is appealing since it effectively reduces the dimensionality of the data and therefore reduces the computational cost of analyzing new data [9]. After obtaining the features set, we need to construct a classifier, which presents a challenge to current researchers.

In recent years, researchers have proposed two categories of approaches to obtain this goal. The first category is supervised classification, such as support vector machine (SVM) [10] and k-nearest neighbors (k-NN) [11]. The other category is unsupervised classification, such as self-organization feature map (SOFM) and fuzzy c-means [12]. While both of these methods achieved satisfactory results, supervised classification performs better than unsupervised classification in terms of classification accuracy (successful classification rate).

The forward neural network (FNN) [13] was chosen as the classifier because it is a powerful tool among supervised classifiers and it can classify nonlinear separable patterns and approximate an arbitrary continuous function [14]. However, to find the optimal parameters of FNN is a difficult task because the search algorithms are easily trapped in local extrema. Recently, there have been many algorithms available to train the FNN, such as back-propagation (BP) algorithm, genetic algorithm (GA) [15], elite genetic algorithm with migration (EGAM) [16], simulating annealing (SA) algorithm, and particle swarm optimization (PSO) [17]. Unfortunately, the BP, GA, SA, PSO algorithms all demand expensive computational costs, and can still be easily trapped into the local best, hence would probably end up without finding the optimal weights of the FNN. In this paper, we use the ABC algorithm to find its optimal weights.

Artificial Bee Colony (ABC) algorithm was originally presented by Karaboga et al. [18] under the inspiration of collective behavior on honey bees with better performance in function optimization problems compared with GA, differential evolution (DE), and particle swarm optimization (PSO) [19]. As is known, normal global optimization techniques conduct only one search operation in one iteration. For example, the PSO carries out a global search at the beginning stage and local search in the ending stage [20, 21], nevertheless, the ABC features in the following advantage in that it conducts both a global search and local search in each iteration, and as a result the probability of finding the optimal is significantly increased, which effectively avoids local optima to a large extent.

However, ABC suffers from following shortcomings: 1) it is easy to be trapped into local minima; 2) and it costs a long time to converge. In order to improve the performance of ABC, we propose a scaled chaotic ABC (SCABC) method based on fitness scaling strategy and chaotic theory to find the optimal parameters of FNN.

The structure of the rest of this paper was organized as follows: Section 2 gives the methodology of this method, including DWT, PCA, K-fold cross validation, and FNN. Section 3 proposes the SCABC algorithm. Experiments in Section 4 demonstrate the effectiveness and rapidness of our proposed SCABC algorithm based on public brain MRI dataset. Finally, Section 5 is devoted to the conclusions.

2. METHODOLOGY

In total, our approach consisted of five stages shown in Figure 1: 1) use DWT to extract features; 2) use PCA to reduce features size; 3) use K-fold stratified cross validation to prevent overfitting; 4) use FNN to construct the classifier; 5) use SCABC to train the FNN.

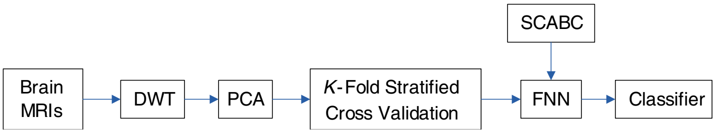


Figure 1. Methodology of our proposed algorithm.

2.1. Discrete Wavelet Transform

The first advantage of using Wavelet Transform (WT) is that it can preserve both the time and frequency information of the signal. Another advantage of WT is that it adopts "scale" instead of traditional "frequency" as it does not produce a time-frequency view but a time-scale view of the signal. The time-scale view is a more natural and powerful way to view data. Using DWT as the feature extraction for brain image classification can be found in Refs. [22–24].

2.2. Feature Reduction

PCA is an efficient tool to reduce the dimension of a data set consisting of a large number of interrelated variables while retaining the most significant variations. It is achieved by transforming the data set to a new set of ordered variables according to their degree of variance or importance. This technique has three effects: (i) it orthogonalizes the components of the input vectors so that they are uncorrelated with each other, (ii) it orders the resulting orthogonal components so that those with the largest variation come first, and (iii) it eliminates the components in the data set that contributing the least variation.

For a 256-by-256 size T2-weighted MR Image, its dimension is $256 * 256 = 65535$; after a three level DWT decomposition, the dimension of the wavelet coefficients is $32 * 32 = 1024$. Therefore, it is still a high computation cost if we directly submit the 1024 dimensional data to classifier. In this paper, we used PCA to reduce the 1024 dimensional data to only 19 principal components.

2.3. Stratified K-fold Cross Validation

One of the problems that occurs during the classifier training is overfitting, where the error on the training set is driven to a very small value, but when new data is presented to the network the error is large. Therefore, cross validation is employed to avoid overfitting. In this paper the K-fold cross validation is applied due to its properties as simple, easy, and using all data for training and validation. The mechanism is to create a K-fold partition of the whole dataset, repeat K times to use K-1 folds for training and a left fold for validation, and finally average the error rates of K experiments.

2.4. Feedforward Neural Network

Neural networks are widely used in pattern classification since they do not need any information about the probability distribution and the a priori probabilities of different classes. The training vectors were presented to the FNN, which is trained in batch mode. The network configuration is supposed as $N_I \times N_H \times N_O$, i.e., a two-layer network with N_I input neurons, N_H neurons in the hidden layer, and N_O output indicating the brain is normal or abnormal.

3. SCALED CHAOTIC ABC

The ABC has proven to perform better than GA, DE and PSO [19] with respect of several standard test functions. Its detailed procedures can be found in Refs. [19, 25]. However, there is no reference discussing the performance of ABC used in FNN. Actually, in the following experimental section we found ABC performs not well for the weights/biases optimization of the FNN. Therefore, we can make further improvements from the following two aspects. The first is to use the fitness scaling strategy; the second is to employ chaotic operator to take place for a random number generator.

3.1. Power-rank Fitness Scaling

Fitness scaling converts the raw fitness scores that are returned by the fitness function to values in a range that is suitable for the selection function. The selection function uses the scaled fitness values to select the bees of the next generation. The selection function assigns a higher probability of selection to bees with higher scaled values.

There exist bundles of fitness scaling methods. The most common scaling techniques are linear scaling, rank scaling, power scaling, top scaling, etc. Among those fitness scaling methods, power scaling finds a solution nearly the most quickly due to improvement of diversity, but it suffers from instability [26]. Meanwhile, rank scaling shows stability on different types of tests [27]. Therefore, a new power-rank scaling method was proposed combing both power and rank strategies as follows

$$fit_i = \frac{r_i^k}{\sum_{i=1}^{N} r_i^k} \tag{1}$$

where r_i is the rank of ith individual bee, N is the number of population. Our strategy contains a three-step process. First, all bees are sorted to obtain the corresponding ranks. Second, powers are computed for exponential values k. Third, the scaled values are normalized by dividing the sum of the scaled values over the entire population.

3.2. Chaotic Operator

The chaotic theory pointed out that minute changes in initial conditions steered subsequent simulations towards radically different final results, rendering long-term prediction impossible in general [28]. Sensitive dependence on initial conditions is not only observed in

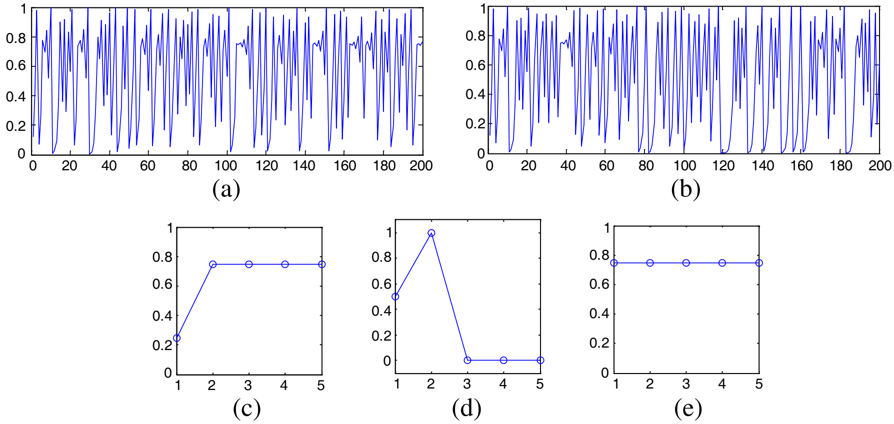


Figure 2. Performances of logistic equation: (a) $x_0 = 0.12345678$; (b) $x_0 = 0.12345679$; (c) $x_0 = 0.25$; (d) $x_0 = 0.5$; (e) $x_0 = 0.75$.

complex systems, but even in the simplest logistic equation. In the well-known logistic equation [29]:

$$x_{n+1} = 4 \times x_n \times (1 - x_n) \tag{2}$$

where $x_0 \in (0, 1)$ and $x_0 \notin \{0.25, 0.5, 0.75\}$. A very small difference in the initial value of x would give rise to a large difference in its long-time behavior as shown in Figures 2(a)–(b). The track of chaotic variable x_n can travel ergodically over the whole space of interest. Figures 2(c)–(e) indicates that the series x_n will lose chaotic property at the points of 0.25, 0.5, and 0.75.

In standard ABC, some random parameters are generated by pseudo-random number generators, which cannot ensure the ergodicity in parameter space because they are pseudo-random. Therefore, chaotic number generator based on formula (2) can force the random parameters nearly absolute random. The detailed procedures of embedding fitness scaling and chaotic operator are listed below.

3.3. Procedures of SCABC

Step 1 Initialize the population of solutions x_{ij} (here i denotes the ith solution, and j denotes the jth epoch, $i = 1, \ldots, SN$, here SN denotes the number of solutions) with $j = 0$

$$x_{i0} = LB + rand(\cdot) \times (UB - LB)(i = 1, \ldots, SN) \tag{3}$$

here LB & UB represents the lower and upper bounds, which can be infinity if not specified. Then, evaluate the population via the specified optimization function;

Step 2 Repeat and let $j = j + 1$;

Step 3 Produce new solutions (food source positions) υ_{ij} in the neighborhood of x_{ij} for the employed bees using the formula

$$\upsilon_{ij} = x_{ij} + \Phi_{ij}(x_{ij} - x_{kj}) \tag{4}$$

Here k is a solution in the neighborhood of i, Φ_{ij} is a chaotic random number in the range $[-1, 1]$ calculated by Equation (2). Evaluate the new solutions;

Step 4 Apply the greedy selection process between x_{ij} and υ_{ij};

Step 5 Calculate the probability values P_{ij} for the solutions x_{ij} by means of their fitness values using the equation

$$P_{ij} = \frac{fit_{ij}}{\sum_{i=1}^{SN} fit_{ij}} \tag{5}$$

Here fit denotes the scaled fitness as shown in Equation (1);

Step 6 Normalize P_{ij} values into $[0, 1]$;

Step 7 Produce the new solutions (new positions) υ_{ij} for the onlookers from the solutions x_{ij} as Step 3, selected depending on P_{ij}, and evaluate them;

Step 8 Apply the greedy selection process for the onlookers between x_{ij} and υ_{ij};

Step 9 Determine the abandoned solution (source), if exists, and replace it with a new randomly produced solution x_i for the scout using the equation

$$x_{ij} = \min_i(x_{ij}) + \varphi_{ij} * \left(\max_i(x_{ij}) - \min_i(x_{ij})\right) \tag{6}$$

Here φ_{ij} is a chaotic random number in $[0, 1]$ calculated by Equation (2).

Step 10 Memorize the best food source position (solution) achieved so far;

Step 11 Go to Step 2 until termination criteria met.

4. EXPERIMENTS AND DISCUSSIONS

The experiments were carried out on the P4 IBM platform with 3 GHz main frequency and 2 GB memory running under the Windows XP operating system. The algorithm was developed on Matlab 2010b.

4.1. Database

The datasets consists of 66 T2-weighted MR brain images in axial plane and 256 × 256 in-plane resolution, which were downloaded from the Harvard Medical School website (http://med.harvard.edu/AANLIB/). The setting of the training images and validation images is shown in Table 1 due to the stratified 6-fold cross validation. Therefore, we ran 6 trials with each 55 (15 normal and 40 abnormal) are used for training and the left 11 (3 normal and 8 abnormal) are used for test.

Table 1. Setting of stratified 6-fold cross validation.

Total No. of images	No. of images in training area (55)		No. of images in testing area (11)	
	Normal	Abnormal	Normal	Abnormal
66	15	40	3	8

The abnormal brain MR images consist of the following diseases: glioma, meningioma, Alzheimer's disease, Alzheimer's disease plus visual agnosia, Pick's disease, sarcoma, and Huntington's disease. A sample of each is shown in Figure 3.

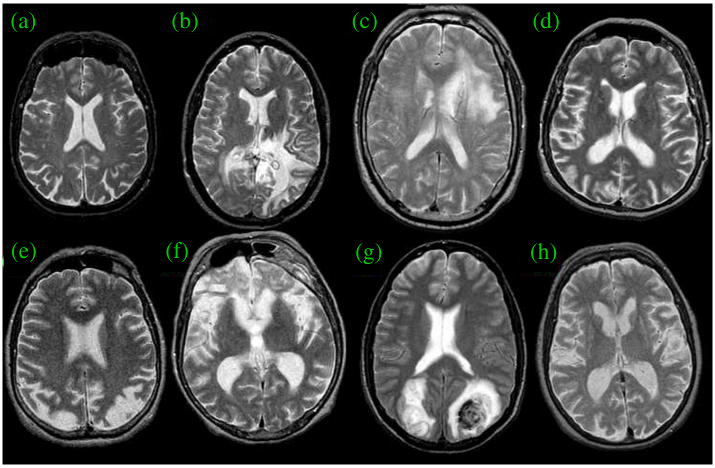


Figure 3. Sample of brain MRIs: (a) Normal brain; (b) glioma; (c) meningioma; (d) Alzheimer's disease; (e) Alzheimer's disease with visual agnosia; (f) Pick's disease; (g) sarcoma; (h) Huntington's disease.

4.2. Algorithm Comparison

After DWT and PCA processing, there are 19 principle components remaining, which were directly sent to the FNN. Thus, the NI is 19 and the NH is determined as 10 according to the information entropy method [30]. Consequently, the structure of the neural network is 19-10-1.

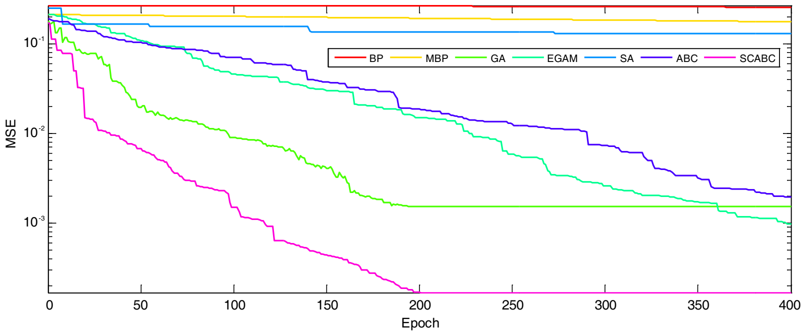
We compare the proposed SCABC algorithm with BP, momentum BP (MBP), genetic algorithm (GA), elite genetic algorithm with migration (EGAM), simulated annealing (SA), and artificial bee colony (ABC). The parameters of GA, EGAM, SA, ABC, and SCABC are obtained using a trial-and-error method and listed in Table 2.

Table 2. Parameters of GA, EGAM, SA, ABC and SCABC.

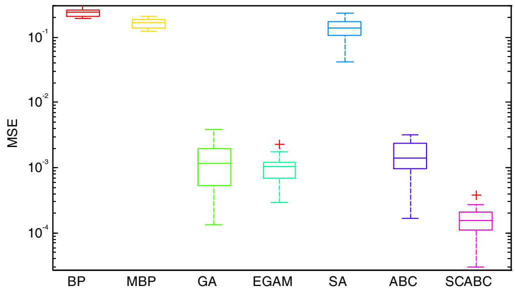
GA		EGAM		SA		ABC/SCABC	
Parameters	Values	Parameters	Values	Parameters	Values	Parameters	Values
SN	20	SN	20	SN	20	SN	20
$MaxEpoch$	400	$MaxEpoch$	400	$MaxEpoch$	400	$MaxEpoch$	400
$P_{Crossover}$	0.8	$P_{Crossover}$	0.8	T_I	100	FN	10
$P_{mutation}$	0.1	$P_{mutation}$	0.1	T_F	0		
		P_{elite}	0.1				
		$P_{migration}$	0.2				

A typical convergence curve is shown in Figure 4(a). Furthermore, the distribution of MSE of 20 runs is shown in Figure 4(b). It indicates that the proposed SCABC performs best with the least mean MSE of 1.67×10^{-4}, the EGAM is the second best algorithm with mean MSE of 9.72×10^{-4}, GA is the third best of 1.5×10^{-3}, and ABC ranks fourth of 2.0×10^{-3}. The detailed data is shown in Table 3.

The BP and MBP does not work well in the MR brain image classification problems because BP/MBP algorithms are designed for the least squares problems that are approximately linear. However, the output neurons in pattern recognition problems are generally saturated. Therefore, global optimization algorithms show more powerful capability in pattern recognition problems. The SA doesn't find the satisfying weights of FNN due to its requirement of large iterative epochs (here we only give each algorithm 400 epochs to converge). Other global optimization methods such as GA, EGAM, ABC, and SCABC all find enough small MSE, moreover, the proposed SCABC can find the least MSE of 20 runs.



(a)



(b)

Figure 4. Training performance: (a) A typical convergence curve; (b) statistical distribution of MSE on 20 runs.

Table 3. Mean and variance of MSE on 20 runs.

Algorithm	Mean MSE	Std Var of MSE	Rank
BP	0.2304	0.0436	7
MBP	0.1765	0.0232	6
GA	1.5×10^{-3}	0.0010	3
EGAM	9.72×10^{-4}	0.0005	2
SA	0.1291	0.0564	5
ABC	2.0×10^{-3}	0.0008	4
SCABC	1.67×10^{-4}	0.0001	1

4.3. Classification Accuracy

The confusion matrix of SCABC on the dataset using stratified 6-fold cross validation is shown in Figure 5. It indicates that the classifier achieves 100% classification accuracy. Moreover, we compared our results with other approaches (DWT + SOM [22], DWT + SVM

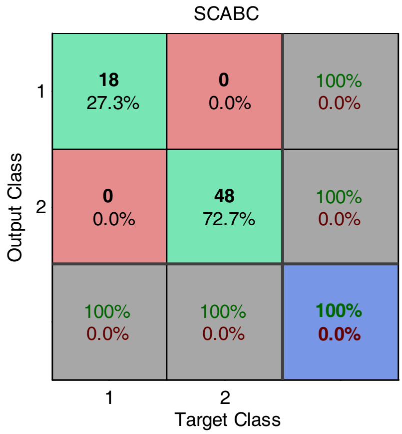


Figure 5. Confusion matrix of the SCABC method.

Table 4. Classification accuracy comparison for the same MRI dataset.

Approach	Classification Accuracy (%)
DWT + SOM [22]	94
DWT + SVM with linear kernel [22]	96
DWT + SVM with radial basis function based kernel [22]	98
DWT + PCA + ANN [23]	97
DWT + PCA + kNN [23]	98
DWT + PCA + ACPSO − FNN [24]	98.75%
DWT + PCA + SCABC − FNN (Our method)	**100%**

with linear kernel [22], DWT + SVM with radial basis function based kernel [22], DWT + PCA + ANN [23], DWT + PCA + kNN [23], DWT + PCA + ACPSO − FNN [24]) described in the recent literature that used the same MRI datasets. The results are shown in Table 4, where DWT denotes discrete wavelet transform, SOM denotes self-organizing map, SVM denotes support vector machine, PCA denotes principle component analysis, ANN denotes artificial neural network, kNN denotes k nearest neighbors algorithm, FNN denotes forward neural network, and ACPSO denotes adaptive chaotic particle swarm optimization. Table 4 indicates that the proposed method had the highest classification accuracy.

5. CONCLUSIONS

In this study we had developed a novel SCABC-FNN classifier to distinguish between normal and abnormal MRIs of the brain. The method obtained 100% classification accuracy on the T2-weighted brain MRI image datasets.

Although the standard ABC is proven better than GA, DE, and PSO in other publications, however the ABC performs worse in the application of training the FNN. Therefore, the performance of different optimization algorithm is dependent on applications.

Future work should focus on the following aspects: 1) the proposed method could be employed for MR images with other contrast mechanisms such as T1-weighted, proton-density-weighted, diffusion-weighted images, and functional MRIs; 2) the features may be improved by using advanced wavelet transforms such as the lift-up wavelet; 3) brain images in sagittal plane or coronal plane can be tested, which needs to redesign and retrain the FNN; 4) 3D brain images are extremely high dimensional, we will test other advanced feature reduction methods; 5) Multi-classification, which focuses on specific brain MRIs disorders, can also be explored; 6) the SCABC can be applied to various industrial fields.

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