An Efficient Technique for Recognition of Odia Numerals Using Particle Swarm Optimized Based FLANN Model with Gradient Feature

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Abstract

One of the challenging tasks in the field of pattern recognition is the recognition of handwritten characters. Handwritten characters are difficult to recognize as compared to printed characters because of large number of variations in writing style. This paper aims to find an efficient system for recognition of Odia handwritten numerals by using PSOFLANN (Particle Swarm Optimized Functional Link Artificial Neural Network) model. All basic steps of character recognition: preprocessing, feature extraction and classification are carried out to achieve the goal. In the preprocessing phase the numeric characters are normalized. In feature extraction phase gradient based approach is used for extraction of features. The extracted features are further reduced by using PCA (Principal Component Analysis). The generated features are then applied to PSOFLANN model for classification. In classification phase two approaches PSO (particle Swarm Optimization) and FLANN (Functional Link Artificial Neural Network) are combined to optimize the weights of FLANN for an efficient recognition system. The system is applied on the standard dataset collected from ISI Calcutta which consists of 1000 samples of Odia handwritten numerals ranging from 0-9. The proposed system achieved 89% accuracy on test dataset which shows the effectiveness of PSOFLANN model for recognition of handwritten Odia numerals.

Keywords: Character Recognition, Preprocessing, Feature Extraction, Classification, Particle Swarm Optimization (PSO), Functional Link Artificial Neural Network (FLANN), Particle Swarm Optimized Functional Link Artificial Neural Network (Psoflann)

INTRODUCTION

Character recognition is a branch of pattern recognition with wide variety of real life applications like automatic data entry, on line form processing, postal mail sorting, bank check processing, passport verification etc. Character recognition is the conversion of printed or handwritten character into machine readable form so that they can be further edited or processed later. It is very difficult to recognize hand written characters as compared to printed characters due to large number of variations in writing style. Fig.1. shows the ten Odia numerals with their corresponding English numerals.

୧	୨	୩	୪	୫	୬	୭	୮	୯	୦
1	2	3	4	5	6	7	8	9	0

Fig.1 Ten Odia Numerals with Corresponding English Numerals

Several authors have applied many techniques in different phase of character recognition to develop a more accurate system. A neural network (NN) approach is proposed in [1] for analysis of signature. In the classification stage the neural network is trained with particle swarm optimization (PSO) algorithm and is tested on two types of forgeries-unskilled and skilled. For harmonic isolation a hybrid Adaptive Neural Network–Particle Swarm Optimization (ANN–PSO) algorithm is proposed in [2]. To increase the fineness of harmonic isolation PSO algorithm is combined with Adaline algorithm. The inertia weight factor of PSO

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is combined along with the weight factor of Adaline in training phase for better results. In [3] the authors have proposed a PSO-BP (Particle Swarm Optimization Back Propagation) neural network for emitter fusion recognition. The training samples are reasonable structured according to the distribution in the interval to determine the network structure and confirm the emitter type through the emitter characteristics parameters. Rajesh K. Agrawal et.al [4] proposed a multiobjective PSO based adaption of optimal neural network topology for the classification of multispectral satellite images. Classification is carried out by using spectral bands. The authors have presented a thorough experimental analysis to investigate the behavior of neural network classifier for given problem. A novel method is proposed in [5] for facial expression recognition. Curvelet transform is used for feature extraction. Support vector machine (SVM) based on particle swarm optimization (PSO) is used for improving the recognition rate. In [6] ANN-PSO (Artificial neural network- particle swarm optimization) hybrid methodology has been used to develop predictive models for simulation and optimization of solid phase extraction method. The method is applied to preconcentration and determination of methylene blue from water samples. Nirban Das et.al [7] have proposed a soft computing paradigm for recognition of handwritten Bangla characters embedded within the framework of two pass approach. A methodology for reading filled in forms of handwritten Bangla characters has been proposed. A good recognition rate is achieved with this method. A multiple classifier method is proposed in [8] for the recognition of offline handwritten Malayalam characters. Gradient and density based approaches are used for feature extraction. For classification two feedforward neural networks are used. Four different combination schemes: Max rule, Sum rule, Product rule and Borda count method are used for combining the results of both these neural networks. A classification accuracy of 81.82% is obtained by the proposed methodology. For recognition of English alphabets a feed forward neural network by two Evolutionary algorithms is proposed in [9] with three different soft computing techniques. A two stage recognition system is proposed by Debananda Padhi et.al [10] for Odia handwritten characters. A feature matrix based on standard deviation and zone centroid average distance is developed for improving the classification accuracy. A feed forward BPNN in two stages is used for feature extraction and recognition. According to similarity of their shapes and features the characters are classified into two groups. A novel approach is proposed in [11] to recognize named entities in Odia corpus. For recognition of specific Named Entity language specific rules are added to the system. For increasing the performance of the system gazetteers and context patterns are added to the system. An attempt is made for recognition of the vowels, consonants, matras, and compound characters of running Odia script in [12]. After segmentation of scanned text, features are extracted by using two-dimensional moments and Hough transform based on topological and geometrical properties. In [13] the authors have proposed particle swarm optimization (PSO) and the Bacterial Foraging Optimization (BFO) for the adaptive identification for efficient identification of complex nonlinear dynamic Plants.

From literature review FLANN has been successively used in many applications with less computational complexity and PSO has been used for solving optimization problem. A hybrid technique plays a very important role in solving very complex problems [14]. A little work has been done on the recognition of characters by using PSO based hybrid technique. In this paper a system is proposed for recognition of Odia handwritten numerals by using a combination of PSO based evolutionary approach and FLANN to optimize the weights of the neural network. The set of optimized weights can be used for the recognition of handwritten numerals.

The paper is organized as follows. Section II describes the dataset, preprocessing and feature extraction phase. Section III describes the classification phase. Simulation and experimental study is discussed in section IV. Conclusion is discussed in section V followed by future scope.

DATASET, PREPROCESSING AND FEATURE EXTRACTION

Dataset

For the proposed model the dataset is collected from Indian Statistical Institute (ISI) Kolkata. The database contains 1000 samples of Odia handwritten numerals ranging from (0-9). All samples of the dataset are categorized into ten classes from (0-9). Each numeral (0-9) appears 100 times in the database. 90% of the dataset is used for training and the rest is used for testing. Fig.2. shows some samples of Odia numerals.

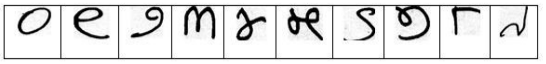

Fig.2 Handwritten Odia Numerals from the Database.

Pre Processing of Data

Pre-processing is the first step of character recognition. This step is carried out to remove all type of irregularities present in the image. It includes the operation like background noise reduction, filtering, original image restoration etc. The images are normalized to a standard pixel size of 64X64 to get uniform images. Then the gray scale image of the data is generated by using Mean filtering method. The gray scale images of the numerals are shown in Fig.3.

Fig.3 Odia Numerals in Gray Scale Image

Feature Extraction

This step is carried out to extract important features from the images. In this paper gradient based approach is used for feature extraction. The Gradient feature represents a directional change in the intensity or color of the numeral. In this paper Robert filter [15],[16] is applied for the extraction of feature. The gradient is calculated from the strength and directions of the pixels. After the generation of feature vector the features are further reduced from 2519 to 75 numbers by using PCA. The direction and strength of gradient so obtained are shown in (Figs. 4(a) and 4(b)) respectively. The direction and strength f (u,v) is calculated as follows

$$\left.\begin{array}{l} g_u = g(u+1, v+1) - g(u,v) \\ g_v = g(u+1, v) - g(u, v+1) \\ Direction: \theta(u,v) = tan^{-1}\left(\frac{g_u}{g_y}\right) \\ Strength: f(u,v) = \sqrt{(g_u)^2 + (g_v)^2} \end{array}\right\} \quad (1)$$

Fig. 4(a) Image showing Direction of Gradient

Fig. 4(b) Image showing Strength of Gradient Classification

For classification two approaches PSO and FLANN are hybridized to find a suitable weight for the neural network so as to best discriminate the classes. The weights of FLANN are optimized by using PSO algorithm. Each sample of the dataset is classified into one of ten classes from 0-9. From the dataset 900 numbers of samples each with 75 input attributes are used for training the proposed PSOFLANN model and the rest are used for testing.

FLANN (Functional Link Neural Network)

FLANN is a single layered ANN structure. FLANN has the advantages of less computational complexity with increased learning rate. FLANN structure has been successively used in many applications [17]. It generates a set of linearly independent functions and evaluates these functions with the pattern as the arguments. In FLANN the pattern dimension space is increased by enhancing the input patterns by using some non linear function. Class separability is more in FLANN structure. In this paper the input signal x(k) is functionally expanded to a number of nonlinear values as given in equation (1). In the proposed model trigonometric expansion is used for functionally expanding the input by using the following equation

$$\begin{aligned} x(k) &= [x(k), \sin\{\pi x(k)\}, \cos\{\pi x(k)\}] \\ &= [x_0(k), x_1(k), x_2(k)] \end{aligned} \quad (1)$$

The weight vector corresponding to k^{th} input vector is given in equation 2

$$h(k) = [h_0(k), h_1(k), h_2(k)]^t \quad (2)$$

The estimated output is computed as

$$y_p(k+1) = x(k) * h(k) \quad (3)$$

Basic of PSO (Particle Swarm Optimization) Algorithm

PSO is a population based algorithm based on the movement and intelligent of swarms [6], [13]. It applies social interaction concept for problem solving. It consists of a number of particles in the search space. Each particle is treated as a point in N-dimensional space. PSO maintains a fixed population size over the search space. Position and velocity are the two attributes of a particle in PSO. The Position and velocity of each particle are initialized randomly. In PSO algorithm there are two criteria: pbest and gBest. The best position attained by an individual particle is known as pBest. The best position attained by the entire population is known as gBest. In N-dimensional space, based on its own experience and entire population each particle updates its position and velocity. Such type of updating policy makes the particles to move towards the gBest. Eventually all particles gather around the gBest point which gives the final solution. Fig.5 shows the flow chart of PSOFLANN model.

Basic steps of PSO algorithm is as follows:

Step1: The velocity and position of all particles are randomly initialized.

Step II: In each iteration the velocity and position of all particles are updated according to the equation

$$\begin{aligned} v_i(t+1) = w * v_i(t) + c_1 * rand * (pBest(t) - x_i(t)) \\ + c_2 * rand * (gBest(t) - x_i(t)) \end{aligned} \tag{4}$$

Where xand v(t) are the position and velocity of particle in t[th] iteration; pBest is the position with the best solution found so far by the particle i; gBest is the position with best solution found so far by the entire population; w is a parameter control the flying dynamics; c_1 and c_2 are factors controlling the related weighting of corresponding terms. Rand is a uniform random number in the range [0, 1]

Step3: The position of all particles are updated by using the equation

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{5}$$

Step IV: Update pBest and gBest when condition is met

$$\begin{aligned} p_i Best = x_i \ \text{ if } f(x_i) < f(p_i Best) \\ g_i Best = g_i \ \text{ if } f(g_i) < f(g_i Best) \end{aligned} \tag{6}$$

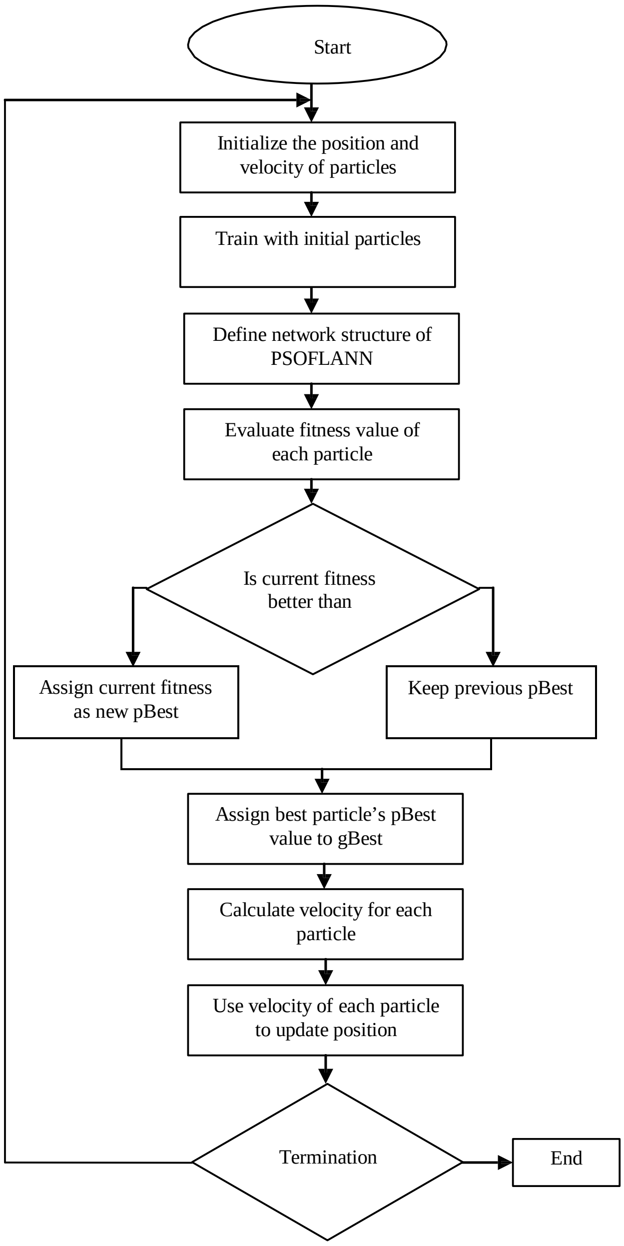

Fig.5 Flowchart of PSOFLANN Model

Step V: Step 2 to step 4 are repeated until termination condition is reached. After termination the gBest gives the best solution.

Weight Optimization by using PSOFLANN Model

The weight optimization of FLANN by using PSO based algorithm is carried out as follows:

Step I: Initially the positions and velocities of the model are choosen corresponding to M particles where each position represents one weight of the FLANN architecture.

Step II: k numbers of input samples are taken and the inputs are functionally expanded trigonometrically to a number of non linear values by using equation 1. For each particle the FLANN is trained. The inputs x_n is passed through the input layer of the FLANN and multiplied with the corresponding weights to get the estimated outputs. The outputs of the FLANN are compared with the target outputs and k errors are produced.

Step III: The fitness is calculated in terms of MSE (Mean Square Error). The MSE for a set of parameters corresponding to n^{th} particle is determined by using the equation 7 and is repeated M times.

$$MSE(n) = \frac{\sum_{i=1}^{k} e_i^2}{k} \quad (7)$$

Step IV: Since the objective is to minimize the MSE PSO is used to optimize the weight of FLANN so as to minimize the error.

Step V: The velocity and position of each bird is updated by using the equation

$$v_i(t+1) = w * v_i(t) + c_1 * rand * (pbest(t) - x_i(t)) + c_2 * rand * (gbest(t) - x_i(t)) \quad (8)$$

$$and \; x_i(t+1) = x_i(t) + v_i(t+1)$$

Step VI: In each iteration the minimum MSE, MMSE is stored which shows the learning behavior of the model. When the MMSE has reached the pre specified level the optimization is stopped. At this step all the particles attend almost identical position, which represents the desired optimized weights of the FLANN.

SIMULATIONS AND RESULTS

All generic phases of character recognition are carried out in simulation part. First preprocessing is carried out to remove all type of irregularities present in the image. The images are normalized to standard size 64X64 pixels. Then mean filtering method is applied on the images for converting them into gray scale images. The feature vectors are obtained by using gradient approach. Further the features are reduced by using PCA from 2519 to 75 numbers. The samples in the dataset are categories into one of 10 classes from (0-9). 900 samples of the dataset are applied to the PSOFLANN model for training purpose and the rest for testing the system. For recognition FLANN is used. PSO algorithm consists of n number of particles where each parameter represents one weight of FLANN. 75 numbers of inputs are applied to the FLANN. The inputs to the FLANN are trigonometrically expanded by using the equation (1). The FLANN is trained for each particle with same weight for all input samples and sigmoid activation function is used to generate the outputs in the output layer. The estimated output is then compared with the desired output for each sample. The errors produced are then used to obtain the MSE. The mean square error is obtained in each iteration by using the fitness of each particle. If the current fitness value is better than pBest, current fitness value is set as pBest. If the pBest is better than gBest, pBest is set as gBest. For each particle the velocity is calculated by using the equation (8). Then the position of the particle is updated by using gBest and velocity. The process of generation is repeated for 500 generations to reach the convergence level. Finally the weights are extracted from the population. The parameters used for PSO are: population size 700, w=0.4. c1=0.7, c2=0.7, number of generations =500. Table 1 and 2 shows the confusion matrix and accuracies of the system for the ten classes on test dataset. From the experimental results the proposed model has achieved a classification accuracy of 87% on test data set.

Table 1 Confusion Matrix for the Recognition of Numerals by Using Psoflann Model

Class	0	1	2	3	4	5	6	7	8	9
0	10	0	0	0	0	0	0	0	0	0
1	0	9	0	0	0	1	0	0	0	0
2	0	0	9	0	0	0	0	1	0	0
3	0	0	0	8	0	0	1	0	1	0
4	0	0	1	0	9	0	0	0	0	0
5	0	0	0	0	0	10	0	0	0	0
6	0	0	0	0	0	0	9	0	1	0
7	0	0	1	0	0	0	0	8	1	0
8	0	0	0	1	0	1	0	0	8	0
9	0	0	0	1	0	0	0	0	0	9

Table 2 Classification Accuracy of PSOFLANN Model

Class	*No of Samples*	*No. of Correct Prediction*	*Accuracy*
0	10	10	100%
1	10	9	90%
2	10	9	90%
3	10	8	80%
4	10	9	90%
5	10	10	100%
6	10	9	90%
7	10	8	80%
8	10	8	80%
9	10	9	90%
Overall Accuracy			89%

CONCLUSION

Two approaches PSO and FLANN are used in this paper for recognition of Odia handwritten numerals. First the preprocessing step is carried out to remove all type of irregularities present in the images. Then the features are extracted from the images by using gradient based approach. The features are further reduced by using PCA from 2519 numbers to 75. For recognition of the numeral FLANN is used. The weights of the FLANN are optimized by using PSO to obtain a suitable set of weights for the neural network. Finally the optimized weights are used in the FLANN to best discriminate the classes. 900 samples from the database are used in the training phase and the rest are used in the testing phase. From experimental study it is observed that the system achieved 89% accuracy on test dataset. Thus PSO based FLANN model can be used successfully for optimizing the weights of FLANN. Such a system can be effectively used for the recognition of Odia numerals.

FUTURE SCOPE

In this paper PSO is used for optimization of weights of the FLANN. There are other evolutionary approaches like GA (genetics Algorithm), DE (Differential Evolution), BFO (Bacterial Foraging Optimization) and ACO (Ant Colony Optimization) which can also be applied for optimization of weights of FLANN. This work is limited to FLANN for recognition. Beside FLANN other NNs (Neural networks) can be employed to achieve a higher recognition rate. The system can be extended for recognition of printed Odia characters and on other standard databases. From literature a number of approaches can be applied on each phase of character recognition to improve the recognition rate. Ensemble of classifiers can be built to improve the classification accuracy of the system. After recognition post processing operations can be applied to further improve the performance of the system.

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