Handwritten Character Recognition Using Generalized Radial Basis Function Extreme Learning Machine with Centers Selection

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***Abstract*—** The handwritten character recognition (HCR) is the major problem in the character recognition domain. There are a lot of methods applied to the handwritten character recognition problems. The "Extreme Learning Machine" (ELM) is the one among them. ELM is the single hidden layer neural networks widely applied in many applications and classification problems. The features of ELM are faster learning method, and it has better performances when compared with other gradient-based neural networks algorithms. In previous research studies, they applied ELM in the field of image processing such as face recognition and face detection. In addition, ELM was applied in many character recognition research studies and it has a good performance. In this paper, this paper used the modified version of generalized radial basis function ELM (MELM-GRBF) to recognize the handwritten characters. Moreover, this paper proposes the improving version of MELM-GRBF for HCR by using the semi-optimization scheme to select the better centers for RBF kernel. The experiments in this paper were applied in three handwritten datasets including Thai characters, Bangla numerals and Devanagari numerals. In the experiment results, the propose method has generally better performances when compared with ELM, MELM-GRBF.

Keywords—Extreme learning machine; handwritten character recognition; generalized radial basis function;

I. INTRODUCTION

Neural network models are widely used in classification and regression problems. Among the whole of usefully and efficiency neural network models, there is a single-hidden-layer feed forward neural networks (SLFNs) that was applied in many problems. From previous research studies, the Gradient-based learning algorithms, such as Back propagation (BP) and Lavenberg-marquad (LM) have been used to train the SLFNs for reasonable performance. However, the major disadvantages of these gradient-based algorithms are high training time and easily trapped in local minima.

A new learning method called "Extreme Learning Machine" (ELM) was proposed in the last decade. This method also based on SLFNs. ELM has the three main steps to learning; firstly, generate input weighs and hidden bias by randomly. Then the networks will calculate the metric outputs of the hidden layer from input weights and hidden bias which fed into the hidden layer. Lastly, compute the output weighs by using More-Penrose (MP) generalized inverse matrices. The learning process has consumed less computational time and many difficult parameters such as; stopping criteria, learning rate, learning epoch and local minima [1, 7] were ignored as well. Although the ELM has several of positive ability, but it also found that ELM tends to require more hidden neurons than traditional gradient-based learning algorithms. Thus, the structure of ELM might be larger than traditional gradient-based learning algorithms.

After the proposed of the traditional version of ELM, a modified version of the ELM for generalized radial basis function neural networks (MELM-GRBF) was proposed [6] and it shows that it has a generalize better performance than traditional ELM. The paper proposed a new training method of ELM called generalized radial basis function (GRBF). This method added the tunable parameter τ in to Gaussian radial basis function and it improved the performance of ELM. The centers of GRBF were randomly selected as the same of input weighs and bias of ELM. The center vectors were fed into hidden layer and they were used to calculate the output of the hidden layer. After that, the output weighs were computed by the MP generalized pseudo inverse. The result of MELM-GRBF is significantly better than the corresponding sigmoidal, hard-limit, triangular basis and radial basis functions.

An evolutionary computing was applied in ELM and proposed in year 2005 [10, 11]. They employed the DE [13] to select input weighs by optimization technique. DE selects the best weighs bias through the fitness function, the root mean square error (RMSE) was considered to find the fitness value. There are no difference with E-ELM and ELM, The MP generalized inverse matrices was used to determine the output weighs of E-ELM. The results of the E-ELM reveal that it can reduce the number of hidden nodes and has higher accuracy when compared with other neural networks. A Few years ago, the evolutionary ELM was proposed in difference optimization technique. They used the Particle Swamp Optimization (PSO) to select the input weighs bias called Improved Particle Swamp Optimization ELM (IPSO-ELM) [12]. Although these evolutionary-ELM methods can improve the performance of the ELMs, but the major problem is they consume a highly computational time when they are facing to the high dimension number problems.

In year 2011 and 2012, there are some research studies reported that ELM can be applied in character recognition and handwriting character recognition [3, 4]. They reported that ELM can archive the minimum error and it has very high accuracy. For these reasons, this paper tries to improve the performance of ELM for HCR. We adopted the good performance method of ELM, the improved version of ELM (MELM-GRBF) and employed the semi-evolutionary concept to select the centers with low RMSE for GRBF. The algorithm is the population-based like DE or PSO. But the propose method some just only focus on the initialize population phase and selects the best ones by fitness value. This study shows that the propose method yields better performances when compared with traditional ELM and MELM-GRBF in Thai handwriting, Bangla numerals and Devanagari numerals HCR domains.

II. PRELIMINARIES

A. Extreme Learning Machine

An Extreme learning machine was proposed by Huang, et al. [7]. They focus on randomize weighs of the hidden layer and weighs biases. The point is yield the zero-error output weighs. Thus, the Moore-Penrose generalized inverse can be employed in implementing the output weighs with zero-error. For instance, we have N distinct arbitrary samples of $(x_i, t_i) \in R^n \times R^m$. A training SLFNs has L hidden nodes and the activation function define as $g(\cdot)$. When the input weighs and hidden biases are randomly generated, the output weighs can approximate by linear system follow as:

$$H\beta = T \tag{1}$$

Where H is the matrix output from hidden layer; H = $\{g(w_j \cdot x_i + b_j)\}$ for i=1, …, L and j=1, …, N. w_j is the input weighs linking between input neurons and hidden neurons; $w_j = [w_{j1}, w_{j2}, \dots, w_{jn}]^T$. $b_j$is the jth hidden neuron bias, and $\beta = [\beta_{j1}, \beta_{j2}, \dots, \beta_{jn}]$ denotes the output weight vector.

In linear system we can determine least-square minimum solution. The minimum norm least-square solution of linear system in (1) is:

$$\beta = H^{\dagger}T \tag{2}$$

Where $H^{\dagger}$is the Moore-Penrose generalized inverse matrices of H.

Some previous works are applied the ELM and wavelet energy to recognize the handwritten character and its learning much faster than traditional popular algorithms for feed forward neural networks. [3] In addition, there is a research study in online sequential extreme learning machine based handwritten character recognition [4]. This paper reveals that the SLFN trained by OS-ELM is used for the classification of Malayalam characters has a high recognition rate (96.83%) with 1200 neurons in the hidden layer.

B. Modified Extreme Learning Machine for GRBF

The ELM with radial basis function (ELM-RBF) has been proposed by Huang, et al [2]. They proposed an ELM method by using RBFs as a RBF activation function. After the ELM-RBFs was proposed, the method name *Modified extreme learning machine for generalized radial basis function neural networks* (MELM-GRBF) was proposed by Francisco, et al [6]. The essence of the method used generalized radial basis function neural networks (GRBF) which removed the constraints of a probability function. The expression of GRBF can be defined by (3).The center vectors c_j was selected inform of pattern of training data, $c_j = (c_{j1}, c_{j2}, \dots, c_{jk})^T$ for a k-dimensional input space.

$$\varphi(x_i, c_j, r_j, \tau_j) = \exp\left(-\frac{||x_i - c_j||^{\tau_j}}{{r_j}^{\tau_j}}\right) \tag{3}$$

In MELM-GRBF method, it has some parameters has been fitted according to the unique characteristics of distances distribution, such as; the width of GRBF (r), and the shape parameter (τ). In addition, there are any user-defined parameters, to define the smallest to be mapped to high value (d_N) and the largest distances in distribution have to be mapped to a low value (d_F). These parameters are related each other and defined as λ. For instance, if λ = 0.05 then d_N = 0.95 (high value) and d_F = 0.05 (low value). The parameters r and τ would be calculated from definable parameter λ, by default it was defined as 0.05.

To calculate τ and r in GRBFNN, the method can use the equations follows by:

$$\tau = \frac{ln\left(\frac{ln(\lambda)}{ln(1-\lambda)}\right)}{ln\frac{d_F}{d_N}} \tag{4}$$

$$r = \frac{d_N}{(-ln(1-\lambda))^{\frac{1}{\tau}}} = \frac{d_F}{(-ln(\lambda))^{\frac{1}{\tau}}} \tag{5}$$

Equation (4) and (5), the parameter d_F was chosen from the nearest two centers, i.e., the d_F of the *i-th* hidden node is $\|c_i - c_j\|$, where j is the nearest hidden node next to node i. Then the parameter d_N is set as $d_N = \sqrt{\delta^2 \times k}$, where k is the number of inputs and δ is a small residual distance in each dimension was set as 0.001.

After the value of τ and r were calculated, we can determine the output from hidden layer by MELM-GRBF algorithm (denote as H).Whole steps of the MELM-GRBF algorithm shows in Fig. 1.

1. Randomly select the data from the training set in the centers of the GRBFs.
2. Calculate the value of d_F by $d_F = ||c_i - c_j||$.
3. Calculate the value of d_N by $d_N = \sqrt{\delta^2 \times k}$.
4. Compute the value of τ by $\tau = \frac{ln\left(\frac{ln(\lambda)}{ln(1-\lambda)}\right)}{ln\frac{d_F}{d_N}}$.
5. Determine the value of r by $r = \frac{d_N}{(-ln(1-\lambda))^{\frac{1}{\tau}}} = \frac{d_F}{(-ln(\lambda))^{\frac{1}{\tau}}}$.
6. Compute the hidden layer output matrix H.
7. Calculate the output weights β by $\beta = \hat{H}^{\dagger}T$

Fig. 1. MELM-GRBF framework [6].

C. Feature Extraction by Histrogram of Oriented Gradient

Feature extractions are an important process for character recognitions. It extracts the outstanding characteristic of each character. Thus, if the feature extraction does not fit to the dataset or method, it may cause the accuracy of recognition is reduced. There are many features extraction methods, somehow, in this paper, we adopted the Histogram of Oriented Gradient (HOG) to extract the character features.

Navneet Daal and Bil Triggs have proposed HOG [10] to detect the human face. They adopted the linear SVM based human detection as a test case. Their research study reveals that the HOG is outperforming those existing feature sets for human face detection.

After the HOG was success in face human detection, in 2013, S. IamSa-at and P. Horata [8] proposed the handwritten recognition used the HOG to extract the features. They compared the results of the method with HOG and without HOG feature extraction. The results show that the HOG features extraction can improve the performance of HCR in Thai HRC domain.

III. SELECTIVE CENTER GRBF FOR EXTREME LEARNING MACHINE

This section presents a hybrid method, we focus to improve the performance MELM-GRBF by using the selective centers strategy. The expression of GRBF Eq. (3) requires four parameters, they are vectors of measurements, center vectors, the width of the GRBF and shape parameters of GRBF denoted as X, C, r and τ respectively. The common algorithm is randomly select center vectors from the pattern of the learning sets, because of this behavior, it may select the inappropriate center vectors and affects the accuracy. The propose hybrid method named "Selective centers generalized radial basis function ELM" (SCGRBF-ELM) has additional steps from the original ELM there are evaluation and selection step. For the additional step will be described in part *B* of this section.

A. Parameters Encoding and Fitness Evaluation

The propose method is a population-based method, the method requires the pattern of populations design for evaluating the fitness values. The pattern of each population (P_i) is composed of a set of center vector adopted by a training data set:

$$P_i = [c_{11}, c_{12}, \dots c_{1n},\ \ c_{21}, c_{22}, \dots c_{2n},\ \ c_{H1}, c_{H2}, \dots c_{Hn}].$$

Where n is the number of input dimensions and H is the number of hidden neurons in the hidden layer.

For the fitness value evaluation, the "root mean square error" (RMSE) on the validation set is only used to the fitness value. After the process, the population with the best fitness value (has the least RMSE) will be selected as the center vectors of the GRBF kernel.

$$Fitness(\cdot) = \sqrt{\frac{\sum_{i=1}^{n_{val}} || \sum_{j=1}^{H} \beta_j \varphi(x_i, c_j, r_j, \tau_j) - t_i ||_2^2}{n_{val}}} \tag{8}$$

where n_{val} is the number of instances in the validation set.

B. Selective Centers GRBF-ELM

The Selective Centers GRBF-ELM (SCGRBF-ELM) is the propose method that used the concept of the optimization scheme to search the optimum centers for GRBF-ELM. Although the optimization methods such as genetic algorithm or differential evolution those can search almost the optimal values, but they consume the high computational time as well. Thus, to reduce the complexity of the optimization method, the propose method ignores some complex process such as mutation and crossover.

The selection of the propose method is divided into three steps; Firstly, define the number of generations and initial the set of center vectors. These center vectors chosen from the training dataset. In this paper, the default population number was set at 50 and use 4 generations. Second step; after the populations were created, The fitness value of each population would be evaluated by Eq. (8). When all populations were evaluated, the center vectors corresponding the best fitness value will be selected to compare with the best center vectors of the next generation. After this step, if the stop criteria is not met, repeat to the first step. Finally, the best center vectors with from whole generation will be selected as the center of the GRBF kernel.

IV. DATA PREPARATION AND EXPERIMENT SETTING

This section, described about all datasets used in our experiments. Then present the experimental design and all of the parameters. And the parameters of each method will be set up in this part. All of the experiments are compiled on Window 8, CPU Intel core i7, Ram DDR3 16GB and implement on Matlab 2014a.

A. Data preparation and preprocessing.

In this paper, we selected the three handwritten character dataset; Thai handwritten characters, Bangla numerals and Devanagari numerals [14, 15, 16] for the experiments. They were divided into training and testing set by 10-fold cross validation. In addition the propose method required the validation set to evaluate the fitness value, thus the some part of the training set for proposing method will be used for the validation set. The detail of the partition of training, validation and testing set shown in TABLE 1.

TABLE I. DETAIL OF THE THREE HAND WRITTEN DATASETS.

Dataset	Classes	Method name	Number of observations		
			Training	Testing	Validation
Thai Handwritten Characters	66	SCGRBF-ELM	595	74	74
		ELM	669	74	-
		ELM-GRBF	669	74	-
Bangla Numerals	10	SCGRBF-ELM	400	50	50
		ELM	450	50	-
		ELM-GRBF	450	50	-
Devanagasi Numerals	10	SCGRBF-ELM	47	5	5
		ELM	52	5	-
		ELM-GRBF	52	5	-

For each image in the data set, they will be resized from the original $X * Y$ pixels image (ori_img) into 32*32 pixels image (resized_img) by equation (9).

$$\text{resized\_img} (i, j) = \text{ori\_img} \left(\frac{X}{32} * i, \frac{Y}{32} * j \right) \quad (9)$$

After the resize process, the images would be extracted their features by HOG. These features extracted by HOG is the data which for classification process. The parameters for HOG were set as follows: block size = 3*3 cells, cell size = 6*6 pixels, block overlap = block size/2, number of orientation histogram binary = 9.

B. The ELMs Parameters and Properties Setting.

The experiment compared the recognition performance between SCGRBF-ELM, ELM [1] and MELM-GRBF [6]. There is some difference between the activation function used in the experiment. The traditional ELM uses sigmoidal as activation function, the expression of the sigmoidal function show in Eq. (10). On the other hand, the activation function of both SCGRBF-ELM and MELM-GRBF are generalized radial basis function which shows in Eq. (3).

$$sig(n) = \frac{1}{1-\exp(-n)} \quad (10)$$

The GRBF kernel was used in MELM-GRBF and SCGRBF-ELM the adjustable parameters λ was set at 0.05, this value should select from [0.04-0.06] [6]. Somehow this parameter is not very sensitive for GRBF kernel algorithms.

For better performance, the values of all of the data sets are scaled in an appropriate range for each method. The data are scaled in range [-1, 1] for ELM and [-2, 2] for MELM-GRBF and SCGRBF-ELM. For all approaches, the number of hidden neurons is set to 500 each.

V. EXPERIMENT RESULTS

This section compared the recognition performance of three methods (ELM, MELM-GRBF and propose method). The recognition rate are from three handwritten character dataset. The results from TABLE 2. show that the training rate of ELM, MELM-GRBF and SCRBFELM on Thai Handwriting dataset are 99.26%, 99.33% and 99.67%. On Bangla Numerals are 98.47%, 98.29% and 99.27%. And the last dataset Devanagari Numerals are 83.95%, 84.07% and 84.96% respectively.

The recognition rate of ELM, MELM-GRBF and SCRBFELM on Thai Handwriting dataset are 96.14%, 96.69% and 97.89%. On Bangla Numerals are 95.02%, 95.96% and 96.36%. And the last dataset Devanagari Numerals are 77.67%, 78.35% and 79.30% respectively.

TABLE II. RECOGNITION RATE COMPARISION OF THREE METHODS.

Data set	Methods					
	ELM		MELMGRBF		SCRBF-ELM	
	Training (%)	Testing (%)±sd.	Training (%)	Testing (%)±sd.	Training (%)	Testing (%)±sd.
Thai Handwritten	99.26	96.14±1.45	99.33	96.69±1.14	**99.67**	**97.89**±1.28
Bangla Numerals	98.47	95.02±3.52	98.29	95.96±2.67	**99.27**	**96.35**±2.72
Devanagari Numerrals	83.95	77.67±2.36	84.07	78.35±1.89	**84.96**	**79.3**±2.21

VI. CONCLUSIONS

This paper study on the handwriting character recognition in Thai handwritten character, Bangla numerals and Devanagasi Numerals. We employed the ELMs to recognize the characters. In addition we improved to the recognition rate of ELM by using the scheme of optimization to select the appropriate input weighs bias (center vector) for the GRBG-ELM. The propose method can yield the better recognition rate for all three datasets (Thai handwritten character, Bangla numerals and Devanagasi Numerals.) when compared with original ELM and MELM-GRBF without centers selection. The propose method also has better training accuracy for all datasets. For standard deviation of recognition rate SCRBF-ELM is better than ELM, yet the STD of MELM-GRBF is better than SCRBF-ELM. From the experiment of these handwritten recognition domain, the semi-optimization scheme can improve the recognition performance of ELMs.

ACKNOWLEDGMENT

This work was supported by the Graduate Education of Computer and Information Science Research Grant from Department of Computer Science, Faculty of Science, Khon Kaen University, 2012.

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