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DEVELOPMENT OF A HYBRID PSO-SVM-BASED OFFLINE OPTICAL CHARACTER RECOGNITION SYSTEM

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ABSTRACT

Optical Character Recognition (OCR) is the mechanical or electronic translation of images of handwritten, typewritten or printed text into machine-editable text. However, with support vector machine, it is difficult to take the proper threshold value and thus end up losing the necessary pixels. On the other hand, SVM only supports atomic concepts rather than complex concepts which makes its applications partially limited. This further makes it difficult to take the scan sample of the forms which includes lots of boxes. In addition, with large size / dimension of features, support vector machine often produce Inaccurate classification results Therefore in this paper, a hybrid of Particle Swarm Optimization (PSO) and Support Vector Machine (SVM) is developed for optical handwritten character recognition. The PSO was used for feature extraction and dimensionality reduction of the resultant features while SVM was used for classification at both training and testing stages. The performance of developed hybrid PSO-SVM for OCR was evaluated using accuracy and time. The evaluation results when compared with support vector machine reveal that the developed hybrid PSO-SVM for OCR outperforms the conventional SVM.

INTRODUCTION

Humans have developed highly sophisticated skills for sensing their environment and taking actions according to what they observe, for example, recognizing a face, understanding spoken words, reading handwriting and distinguishing fresh food from its smell via adaptive pattern recognition capability. Pattern recognition aims to make the process of learning and detection of patterns explicit, such that it can partially or entirely be implemented on computers. Automatic (machine) recognition, description, classification (grouping of patterns into pattern classes) have become important problems in a variety of engineering and scientific disciplines such as biology, psychology, medicine, marketing, computer vision, artificial intelligence and remote sensing.

In almost any area of science in which observations are studied but the underlying mathematical or statistical models are not available, pattern recognition can be used to support human concept acquisition or decision making (Kumar, Koshti and Govilkar, 2014). Given a group of objects, there are two ways to build a classification or recognition system: supervised, that is, with a teacher, or unsupervised, without the help of a teacher. Interest in pattern recognition has been renewed recently due to emerging applications which are not only challenging but also computationally more demanding such as data mining, document classification, organization and retrieval of multimedia databases. However, one of the most trending pattern classifier is the Support vector machine (SVM). SVM is a computer algorithm that learns by example to assign labels to objects. For instance, an SVM can learn to recognize fraudulent credit card activity by examining hundreds or thousands of fraudulent and non-fraudulent credit card activity reports.

Alternatively, an SVM can learn to recognize handwritten digits by examining a large collection of scanned images of handwritten zeroes, ones and so forth. SVMs have also been successfully applied to an increasingly wide variety of biological applications. A common biomedical application of support vector machines is the automatic classification of microarray gene expression profiles. However, SVM suffers from high misclassification rate when the dimension of the features is very large (Fagbola, Olabiyisi and Adigun, 2012). To this end, modified and improved versions of SVM are sought-after requirements for accurate recognition of optical handwritten characters.

Optical character recognition (OCR) is often used to convert different types of documents, such as scanned paper documents, PDF files or images captured by a digital camera into editable and searchable data. Basically, there are three types of OCR. These include the offline handwritten text, online handwritten text and the machine printed text (Kumar, Koshti and Govilkar, 2014).

a. **Offline Handwritten Text:** The text produced by a person by writing with a pen/ pencil on a paper medium and which is then scanned into digital format using scanner is called Offline Handwritten Text.
b. **Online Handwritten Text:** Online handwritten text is the one written directly on a digitizing tablet using stylus. The output is a sequence of x-y coordinates that express pen position as well as other information such as pressure (exerted by the writer) and speed of writing.
c. **Machine Printed Text:** Machine printed text can be found commonly in daily use. It is produced by offset processes, such as laser, inkjet and many more.

In a related manner, Particle Swarm Optimization (PSO) has been a fundamental metaheuristic approach for optimizing the performance of most conventional algorithms. PSO is a global optimization method invented by Eberhart and Shi in 2001 based on social conduct of birds (Clerc, 2002). PSO incorporates swarming conduct identified in schools of fish, swarms of bees, flocks of birds from which the idea is emerged (Eberhart, 2001). In this paper, a hybrid PSO-SVM classification technique is developed for the optical handwritten character recognition system.

2.0 Related Works

Optical character recognition allows for automatically recognizing characters through an optical mechanism. It is capable of recognizing both handwritten and printed text. However, anymber of works recently developed are discussed. Bansal and Sharma (2010) developed an isolated handwritten words segmentation technique in Gurmukhi Script. The work elaborates the segmentation of various irregular text words written in Gurumukhi script as well as words containing skewed, broken, irregular headline, touching and overlapped characters. Some of the new techniques like counter tracing methods are used along with horizontal and vertical projections. In the same vein, Garg, Kaur and Jindal (2011) worked on the segmentation of half characters in Handwritten Hindi.

Text Character recognition is an important stage of any text recognition system. In Optical Character Recognition (OCR) system, the presence of half characters decreases the recognition rate. Due to touching of half character with full characters, the determination of presence of half character is very challenging task. The work leveraged on the structural properties of text to segment the half characters in handwritten Hindi text. Based on the results obtained, the developed algorithm achieves an accuracy of 83.02% for half characters in handwritten text and 87.5% for printed text.

Kumar, Koshti and Govilkar (2014) developed a segmentation technique for handwritten Gurumukhi characters defining the whole process for segmentation including digitization process and pre-processed techniques. Water Reservoir method was applied for identification and segmentation of touching characters. Kumar and Singh (2011) also developed an algorithm to detect and segment Gurmukhi Handwritten text into lines, words and characters. To get the character, the coordinates of detected lines and words are used. Their character segmentation process was divided in two part: (i) to get the segmented region R (ii) to check, if R has a meaningful symbol or not. This can be a reverse approach to ensure correct segmentation, that is, if R does not have a meaningful symbol then R is readjusted. It was tested on different documents and the results obtained are remarkable. More importantly, it was able to interpret the lines which were having some characters in the lower zone almost correctly.

Kumar, Jindal and Sharma (2010) developed a variable sized window technique for the segmentation of scanned document image which is treated as one large window. The large window was splitted into smaller windows as lines and once the lines are recognized then each window consisting of a line is used to recognize a word that is present in a line, and at the end, character is recognized. Patil, Rajharsh and Rohini (2015) developed an offline handwritten alphabetical character recognition system using multilayer feed forward neural network. Others include but not limited to OCR using hierarchical optimization (Kirill, Igor and Heinz, 2007), hand written English character recognition using column-wise segmentation of image matrix (Rakesh and Manna, 2012), Devnagari script character recognition using genetic algorithm (Vedgupt and Rao, 2013), scene text recognition in mobile applications by character descriptor and structure configuration (Chucai and Yingli, 2014), an enhanced artificial neural network-based offline signature verification and recognition system (Shilpa and Anagha, 2013) and an offline signature verification and recognition based on four speed stroke angle (Sudhakar, 2009).

3.0 MATERIALS AND METHOD

In this paper, the basic steps used in developing the PSO-SVM-based Optical Character Recognition system include the image acquisition, preprocessing, feature extraction, training and recognition.

3.1 Support Vector Machine (SVM)

Support Vector Machines (SVMs) are learning systems that utilize a hypothesis space of separating functions in a high dimensional feature space. The algorithm is depicted as follows (Fagbola, Olabiyisi and Adigun, 2012):

Input: sample *x* to classify, Training set

$T = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$

Output: decision $y_j \in$ [-1,1]

Compute SVM solution *w*, *b* for data set with inputed labels

Compute outputs $y_i = (w, x_i) + b$ for all x_i in positive bags

Set y_i = sign (y_i) for every $i \in [-1,1]$

For (every positive bag Bi)

If $(\sum_{i \in I} \frac{1+y_i}{2} == 0$

Compute $i^* = \arg max_{i \in I}\, y_i$

Set y_i =1

End

While (inputed labels have changed)

Output (*w*, *b)*

Put values *w*, *b* in y_i and get the result y_i

3.2 Particle Swarm Optimization (PSO)

PSO uses swarm to perform searches in a given population. The population comprises particles, which represent a metaphor of birds in flocks. These particles were amended through iteration process (Adigun, Fagbola and Adegun, 2014). In PSO, a set of particles or solutions traverse the chase space with energy based on their experience and that of their neighbours in the community. This progression is subjected to repeated iteration until a perfect solution is obtained. The basic operation of the PSO is detailed beneath (Adigun, Fagbola and Adegun, 2014; Karl, 2005; Lin *et al.*, 2008).

Step 1: *Initialization.* The speed rate and location of all features are set to within specified ranges.

Step 2: *Velocity updating.* Speed rate Updating. The pace of all features are renewed in each trial according to:

$$V_i = WV_i + C_1R_1(P_{i,best} - P_i) + C_2R_2(g_{i,best} - P_i) \qquad (1)$$

where P_i and V_i represent the location and rate of speed of feature i, separately; $P_{i,best}$ and $g_{i,best}$ translates to the position with the 'best' objective value by particle i and the entire populace separately; is the factor controlling the flying dynamics; R1 and R2 mean random variables within the boundary [0, 1]; C_1 and C_2 translates to parameters controlling the weighting of related terms. The inclusion of random variables enhances the PSO with the power of stochastic hunting. The weighting factors, C_1 andC_2, compromise inevitable tradeoff between discovery and utilisation After updating, V_i is checked to avoid excess random movement within the specified range.

Step 3: *Position Updating.* Consider a unit time interval between successive rehearsal, the locations of all features are renewed according to:

$$P_1 = P_i + V_i \qquad (2)$$

After updating, P_i is checked to ensure precision.

Step 4: Memory updating. Update $P_{i,best}$ and $g_{i,best}$ when requirement is met.

$P_{i,best} = P_i$ If f (P_i) > f ($P_{i,best}$)

$g_{i,best} = g_i$If f (g_i) > f ($g_{i,best}$) (3)

Where *f* (*x*) represent the objective function.

Step 5: Termination-Checking. The algorithmic process iterates Steps 2 to 4 until certain demands are met. After termination, the values of g_{best} and f (g_{best}) are reported as its optimum solution.

3.3 Design of the Proposed SVM-PSO Technique for Offline Optical Character Recognition

The design of the proposed SVM-PSO technique for offline optical character recognition is presented in Figure 1. This consists of the data acquisition phase for training and testing the PSO-SVM based OCR, pre-processing via binarization, feature extraction using PSO and classification using SVM.

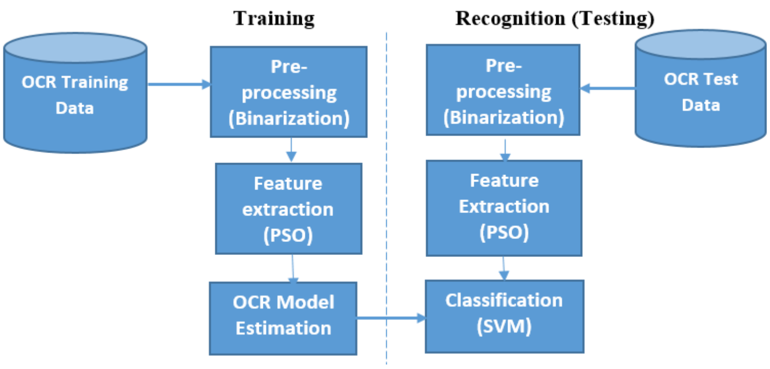

Figure 1: The Block Diagram of the Proposed SVM-PSO technique for Offline Optical Character Recognition.

3.4 Implementation of the Proposed SVM-PSO for Offline Optical Character Recognition

Microsoft.Net framework and C# programming language were used for the implementation of the PSO-SVM-based OCR developed in this paper due to their platform-independent and scalability characteristics.

3.4.1 Preprocessing

This is done to boost the probabilities of undefeated recognition. Through binarization, segmentation of fixed-pitch fonts is accomplished comparatively just by orientating the image to an identical grid supported wherever vertical grid lines can least typically ran into black areas.

3.4.2 Feature Extraction

Feature extraction is performed after preprocessing step is completed successfully. The PSO algorithm is designed for obtaining character as solutions in order to reduce the high number of characters to be later classified. Particle swarm optimization was used for feature extraction. The features extracted include (1) Height of the character; (2) Width of the character; (3) Numbers of horizontal lines present—short and long; (4) Numbers of vertical lines present—short and long; (5) Numbers of circles present (6) Numbers of horizontally oriented arcs; (7) Numbers of vertically oriented arcs; (8) Centroid of the image; (9) Position of the various features; (10) Pixels in the various regions.

3.4.3 Training and Recognition

Support Vector Machines, a technique derived from statistical learning theory, is used to classify points by assigning them to one of two disjoint half spaces. So, SVM performs mainly a (binary) 2-class classification. For linearly separable data, SVM obtains the hyper plane which maximizes the margin (distance) between the training samples and the class boundary. For non-linearly separable cases, samples are mapped to a high dimensional space where such a separating hyper plane can be found. The assignment is carried out by means of a mechanism called the kernel function. The SVM classifier is used whenever the fitness evaluation of a tentative character subset is required. However, the system is trained using the foreground and background color of the character. Figures (2 and 3) present sample training process of the PSO-SVM based OCR with some characters while Figures (4 and 5) present sample recognition (testing) process of the PSO-SVM-based OCR.

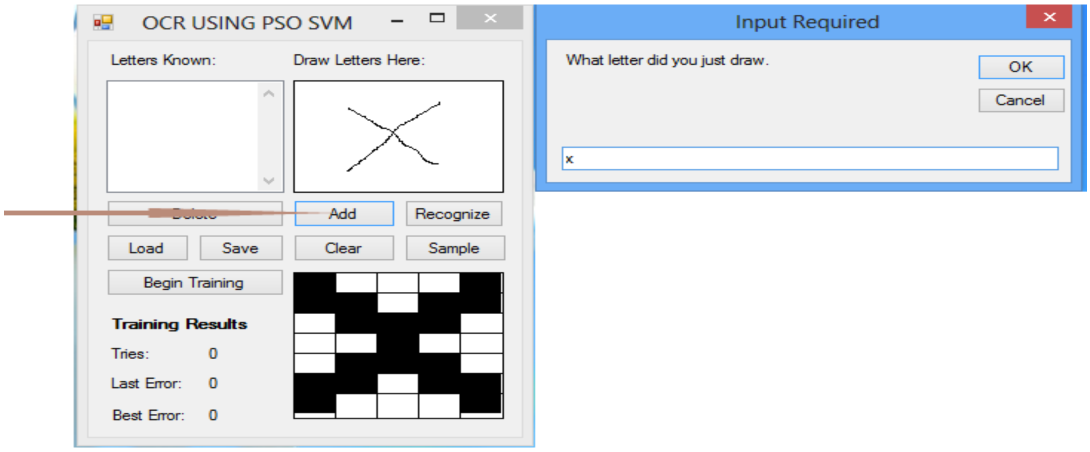

Figure 2: Training PSO-SVM-based OCR to Recognize Character X.

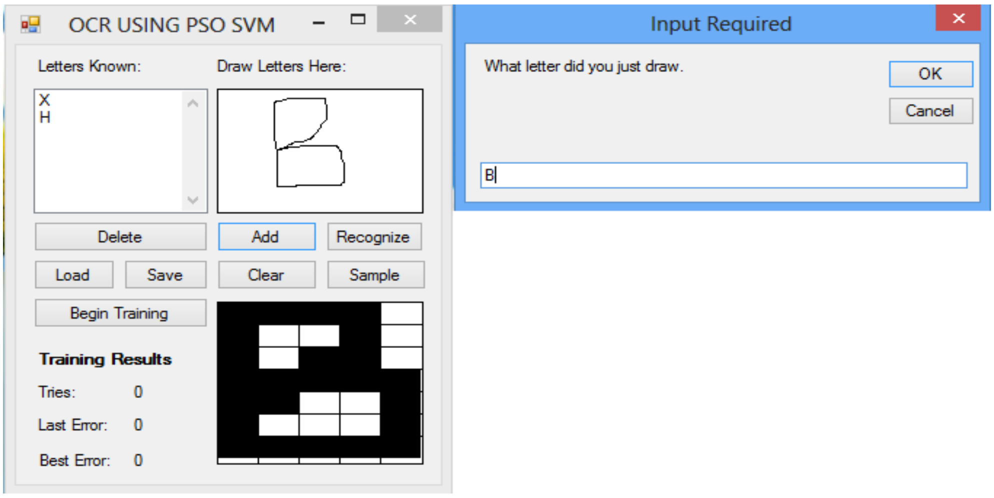

Figure 3: Training to Recognize Character B.

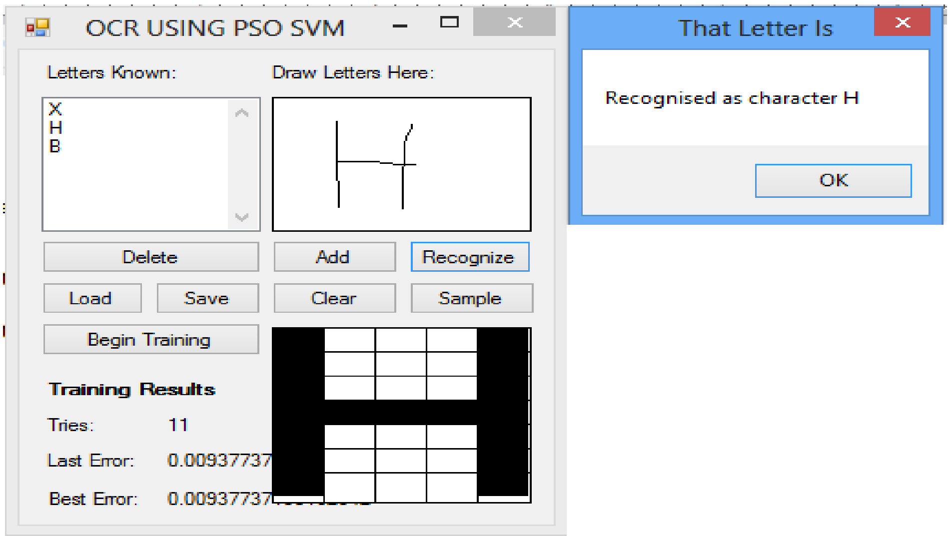

Figure 4: Recognized Character H.

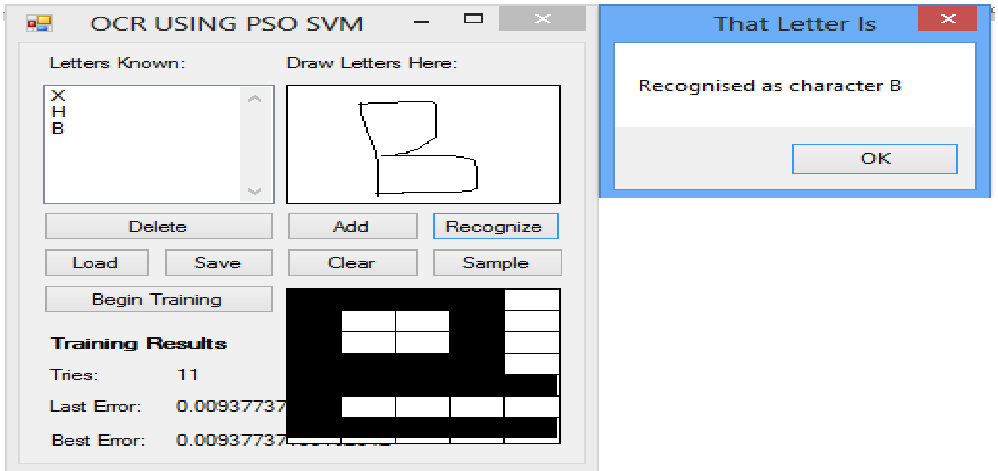

Figure 5: Recognizing Character B.

3.5 Performance Evaluation Metrics

The performance evaluation metrics considered in this paper are recognition accuracy and recognition time.

i. **Recognition Accuracy:** This is the percentage of all characters that are correctly recognition over the total characters identified.

ii. **Recognition Time**

This is total finite time in seconds for the OCR system to recognize the character and display results.

4.0 Experimental Results and Discussion

The summary of the experimental results obtained for the developed PSO-SVM-based optical character recognition system is presented in Table 1.

Table 1: Summary of Experimental results obtained.

Algorithms	Recognition Accuracy (%)	Recognition Time (s)
Support Vector Machine	87	457
Hybrid PSO-SVM	93	202

SVM produced an accuracy of 87% at a recognition time of 457s while the hybrid PSO-SVM produced a recognition accuracy of 93% at a recognition time of 202s. This indicates that the performance of conventional classifier can be improved by combining them with metaheuristic optimizers.

5.0 Conclusion and Future Work

In this paper, a hybrid PSO-SVM algorithm for recognizing optical character was developed. Reaching an accuracy rate of 93% during testing with sets corresponding to small and capital letters, SVM-PSO based OCR performs more accurately and efficiently than SVM that achieved 87% accuracy at the expense of computational efficiency. Hence, enhancing the conventional recognition systems with metaheuristic optimizers is a key to extending their performance capability and efficiency. However, future works can consider the development of OCR based on modified metaheuristic algorithms and/or hybridization of same for improved OCR performance. Automatic determination of the optimal parameters of the kernel functions of the hybrid PSO-SVM can also be investigated.

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