Recognition of Handwritten Numerals using RBF-SVM Hybrid Model

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Abstract: *One of the major developments in machine learning in the past decade is the ensemble method, which finds highly accurate classifier by combining many moderately accurate component classifiers. This paper addresses using an ensemble of classification methods for recognizing totally unconstrained handwritten numerals. Due to a great variety of individual writing styles, the problem is very difficult and far from being solved. In this research work, new hybrid classification method is proposed by combining classifiers in a heterogeneous environment using arcing classifier and their performances are analyzed in terms of accuracy. A classifier ensemble is designed using Radial Basis Function (RBF) and Support Vector Machine (SVM). Here, modified training sets are formed by resampling from original training set; classifiers constructed using these training sets and then combined by voting. Empirical results illustrate that the proposed hybrid systems provide more accurate handwriting recognition system*.

Keywords: *Handwriting recognition, ensemble, RBF, SVM classification, accuracy*.

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1. Introduction

Optical Character Recognition (OCR) is a branch of pattern recognition and also a branch of computer vision. OCR has been extensively researched for more than four decades. With the advent of digital computers, many researchers and engineers have been engaged in this interesting topic. It is not only a newly developing topic due to many potential applications, such as bank check processing, postal mail sorting, automatic reading of tax forms and various handwritten and printed materials, but it is also a benchmark for testing and verifying new pattern recognition theories and algorithms. In recent years, many new classifiers and feature extraction algorithms have been proposed and tested on various OCR databases and these techniques have been used in wide applications. Numerous scientific papers and inventions in OCR have been reported in the literature. It can be said that OCR is one of the most important and active research fields in pattern recognition. Today, OCR research is addressing a diversified number of sophisticated problems. Important research in OCR includes degraded (heavy noise) Omni font text recognition and analysis/recognition of complex documents (including texts, images, charts, tables and video documents). Handwritten numeral recognition, (as there are varieties of handwriting styles depending on an applicant's age, gender, education, ethnic background, etc., as well as the writer's mood while writing) is a relatively difficult research field in OCR.

In the area of character recognition, the concept of combining multiple classifiers is proposed as a new direction for the development of highly reliable character recognition systems [25] and some preliminary results have indicated that the combination of several complementary classifiers will improve the performance of individual classifiers [14, 25]. The primary objective of this paper is ensemble of Radial Basis Function (RBF) and Support Vector Machine (SVM) is superior to individual approach for recognizing totally unconstrained handwritten numerals in terms of classification accuracy. The rest of this paper is organized as follows: Section 2 describes the related work. Section 3 presents hybrid intelligent handwriting recognition system and section 4 explains the performance evaluation measures. Section 5 focuses on the experimental results and discussion. Finally, results are summarized and concluded in section 6.

2. Related Works

In the past several decades, a wide variety of approaches have been proposed to attempt to achieve the recognition system of handwritten numerals. These approaches generally fall into two categories: statistical method and syntactic method [24]. First category includes techniques such as template matching, measurements of density of points, moments, characteristic loci and mathematical transforms. In the second category, efforts are aimed at capturing the essential shape features of numerals, generally from their skeletons or contours. Such features include loops, endpoints, junctions, arcs, concavities and convexities and strokes.

Suen *et al*. [24] proposed four experts for the recognition of handwritten digits. In expert one, the skeleton of a character pattern was decomposed into branches. The pattern was then classified according to the features extracted from these branches. In expert two, a fast algorithm based on decision trees was used to process the more easily recognizable samples and a relaxation process was applied to those samples that could not be uniquely classified in the first phase. In expert three, statistical data on the frequency of occurrence of features during training were stored in a database. This database was used to deduce the identification of an unknown sample. In expert four, structural features were extracted from the contours of the digits. A tree classifier was used for classification. The resulting multiple-expert system proved that the consensus of these methods tended to compensate for individual weakness, while preserving individual strengths. The high recognition rates were reported and compared favorably with the best performance in the field.

The utilization of the SVM classifier has gained immense popularity in the past years [6, 19]. SVM is a discriminative classifier based on Vapnik’s structural risk minimization principle. It can be implemented on flexible decision boundaries in high dimensional feature spaces. Generally, SVM solves a binary (two-class) classification problem and multi-class classification is accomplished by combining multiple binary SVMs. Good results on handwritten numeral recognition by using SVMs can be found in [10].

Artificial Neural Networks (ANN), due to its useful properties such as: Highly parallel mechanism, excellent fault tolerance, adaptation and self-learning, have become increasingly developed and successfully used in character recognition [2, 7]. The key power provided by such networks is that they admit fairly simple algorithms where the form of nonlinearity that can be learned from the training data. The models are thus extremely powerful, have nice theoretical properties, and apply well to a vast array of real-world applications.

To study the recognition of off-line handwritten Chinese character [17] constructed a kind of decision-making information system. The character feature is considered as condition attribute, and the true value of character samples is regard as decision attribute. A heuristic algorithm of the attribute reduction based on variable precision rough set is presented for reducing the redundancy features. The attribute importance is defined based on β approximation dependence it is taken as heuristic information in that algorithm. In the case of no rule can be fully matched in the process of recognition, to improve the identifiability and correct classification rate of handwritten Chinese character, a kind of rules fusion method based on weighted rules confidence is proposed. The experiment results show that the method is feasible and effective.

Naeimizaghiani *et al.* [21] presents a enhanced feature extraction method which is a combination and selected of two feature extraction techniques of Gray Level Co occurrence Matrix (GLCM) and Edge Direction Matrixes (EDMS) for character recognition purpose. It is apparent that one of the most important steps in a character recognition system is selecting a better feature extraction technique, while the variety of method makes difficulty for finding the best techniques for character recognition. The dataset of images that has been applied to the different feature extraction techniques includes the binary character with different sizes. Experimental results show the better performance of proposed method in compared with GLCM and EDMS method after performing the feature selection with neural network, bayes network and decision tree classifiers.

Wang *et al.* [28] researches on the issue of computer recognition to the handwritten character images, including lowercase letters and Arabic numerals.

Das *et al.* [9] have proposed Hidden Markov Model (HMM) based system for English HCR in their literature. They have employed global as well as local feature extraction methods. Global feature involves four gradient features, six projection features and four curvature features and to extract local features, image is divided in to nine equal blocks and 4 gradient features are calculated from each block, so total of 36 features are extracted. So, overall feature vector contains 50 features per character. O= [G(4) P(6) C(4) L(36)], where G, P, C and L represents global gradient, projection, curvature and local gradient features respectively. Number in parenthesis represents number of respective features. HMM is trained using these feature and experiment is carried out. Post processing is also applied after recognition phase of HMM to highly confused group of characters like N and M, O and Q, C and O etc. For each group new feature is calculated to discriminate characters within the group.

Postal address recognition system for Arabic language is proposed in [8]. Writing translates style of writing, Mood and personality of the writer, which makes it difficult to characterize. From scanned envelop, printed boarder and stamp logo are suppressed. Address is located and using histogram method, lines, words and characters are segmented. Temporal order of strokes can be helpful for robust recognition. In literature, way of temporal order reconstruction is proposed. End stroke point, Branching point and Crossing point are detected from city name. Elliptical model is applied on pre-processed digit or character and matching process is applied.

Om Prakash *et al*. [22] have proposed zone based hybrid feature extraction method. Euler number concept is used to improve speed and accuracy. Thresholding, filtering and thinning operations are performed as a part of pre-processing. Segmentation can be classified into three broad categories: Top down, bottom up and hybrid techniques. In proposed method segmented character is resized to 90×60. After calculating Euler number from this image, character is divided in to 10×10 pixel 54 zones. Each zone value is replaced by average intensity value and is used as feature values 9 and 6 features are extracted by averaging values row wise and column wise, so it forms total 69 features. A FFBPNN with configuration 69-100-100-26 is used for classification.

Xu *et al.* [30] proposed four combining classifier approaches according to the levels of information available from the various classifiers. The experimental results showed that the performance of individual classifiers could be improved significantly. Huang and Suen [15, 16] proposed the Behavior-Knowledge Space method in order to combine multiple classifiers for providing abstract level information for the recognition of handwritten numerals. Lam and Suen [20] studied the performance of combination methods that were variations of the majority vote. A Bayesian formulation and a weighted majority vote (with weights obtained through a genetic algorithm) were implemented, and the combined performances of seven classifiers on a large set of handwritten numerals were analyzed.

Samoud *et al.* [23] proposed hybrid method is based on Hough Transform (HT) and Mathematical Morphology (MM) tools named HT-MM. It is firstly used to extract handwritten text blocks from a complex document [3]. It is then applied to segment the extracted handwritten text in sub-words, and the sub-word in characters too.

Freund and Schapire [11, 12] proposed an algorithm the basis of which is to adaptively resample and combine (hence the acronym--arcing) so that the weights in the resampling are increased for those cases most often misclassified and the combining is done by weighted voting. Previous work has demonstrated that arcing classifiers is very effective for RBF-SVM hybrid system [13].

In this paper, a handwriting recognition system is proposed using RBF, SVM and the effectiveness of the proposed RBF-SVM hybrid system is evaluated by conducting several experiments on U.S. Zip code database. The performance of the RBF-SVM hybrid classifier is examined in comparison with standalone RBF and standalone SVM classifier.

3. Hybrid Intelligent Handwriting Recognition System

This section shows the proposed RBF-SVM hybrid system which involves RBF and SVM as base classifiers.

3.1. RBF-SVM Hybrid System

The proposed hybrid intelligent handwriting recognition system is composed of four main phases; preprocessing phase, feature extraction phase, classification phase and combining Phase.

3.1.1. Zip Codes Dataset Pre-Processing

Locating the zip code on the envelope and separating each digit from its neighbors, a very hard task in itself, was performed by postal Service contractors [27]. At this point, the size of a digit image varies but is typically around 40 by 60 pixels. A linear transformation is then applied to make the image fit in a 16 by 16 pixel image. This transformation preserves the aspect ratio of the character, and is performed after extraneous marks in the image have been removed. Because of the linear transformation, the resulting image is not binary but has multiple gray levels, since a variable number of pixels in the original image can fall into a given pixel in the target image. The gray levels of each image are scaled and translated to fall within rang -1 to 1.

3.1.2. Feature Extraction

During the past decades considerable research has been done to define and extract the good quality features. Generally speaking, features used to solve a pattern recognition problem can be grouped into two wide groups: Numerical features and structural features. Numerical features are generally used to deduce the global information while the structural features are used to derive the global structure of a pattern. Algorithms to extract the numerical features are easy to implement but these features are highly sensitive to style variations, translation and rotation, and do not provide the structural description of a pattern. The use of structural features reflecting the geometrical and topological properties of a pattern has been suggested to account for the variation in pattern. Commonly used structural features are strokes, bays (cavities), end points, intersections of line segments, and loops. These feature sets and the methods of extracting them are presented in [1] for details.

3.1.3. Existing Classification Methods

3.1.3.1. RBF Neural Network

The RBF design involves deciding on their centers and the sharpness (standard deviation) of their Gaussians. Generally, the centres and Standard Deviations (SD) are decided first by examining the vectors in the training data [5]. RBF networks are trained in a similar way as MLP. The output layer weights are trained using the delta rule. The RBF networks used here may be defined as follows:

- RBF networks have three layers of nodes: Input layer, hidden layer, and output layer.
- Feed-forward connections exist between input and hidden layers, between input and output layers (shortcut connections), and between hidden and output layers. Additionally, there are connections between a bias node and each output node. A scalar

weight is associated with the connection between nodes.

- The activation of each input node (fanout) is equal to its external input where is the element of the external input vector (pattern) of the network (denotes the number of the pattern).
- Each hidden node (neuron) determines the Euclidean distance between "its own" weight vector and the activations of the input nodes, i.e., the external input vector the distance is used as an input of a RBF in order to determine the activation of node. Here, Gaussian functions are employed. The parameter of node is the radius of the basis function; the vector is its center.
- Each output node (neuron) computes its activation as a weighted sum The external output vector of the network, consists of the activations of output nodes, i.e., The activation of a hidden node is high if the current input vector of the network is "similar" (depending on the value of the radius) to the center of its basis function. The center of a basis function can, therefore, be regarded as a prototype of a hyper spherical cluster in the input space of the network. The radius of the cluster is given by the value of the radius parameter.

3.1.3.2. Support Vector Machine

The SVM is a recently developed technique for multi dimensional function approximation. The objective of SVMs [26] is to determine a classifier or regression function which minimizes the empirical risk (that is the training set error) and the confidence interval (which corresponds to the generalization or test set error).

Given a set of N linearly separable training examples $S=\{x_i \in R^n | i= 1, 2, ..., N\}$, where each example belongs to one of the two classes, represented by $y_i \in \{+1, -1\}$, the SVM learning method seeks the optimal hyper plane $w.x+b= 0$ as the decision surface, which separates the positive and negative examples with the largest margins. The decision function for classifying linearly separable data is:

$$f(X) = sign\left(W.X + b\right) \tag{1}$$

Where w and b are found from the training set by solving a constrained quadratic optimization problem. The final decision function is:

$$f(x) = sign\left(\sum_{i=1}^{N} a_i y_i (x_i .x) + b\right) \tag{2}$$

The function depends on the training an example for which a_j is non-zero. These examples are called SVs. Often the number of SVs is only a small fraction of the original data set. The basic SVM formulation can be extended to the non linear case by using the nonlinear kernels that maps the input space to a high dimensional feature space. In this high dimensional feature space, linear classification can be performed. The SVM classifier has become very popular due to its high performances in practical applications such as text classification and pattern recognition. The SV regression differs from SVM used in classification problem by introducing an alternative loss function that is modified to include a distance measure. Moreover, the parameters that control the regression quality are the cost of error C, the width of tube ε and the mapping function ϕ.

In this research work, the values for polynomial degree will be in the range of 0 to 5. In this work, best kernel to make the prediction is polynomial kernel with epsilon=1.0 E-12, parameter d=4 and parameter c=1.0. A hybrid scheme based on coupling two base classifiers using arcing classifier adapted to data mining problem is defined in order to get better results. The main originality of proposed approach relies on associating two techniques: Extracting more information bits via specific linguistic techniques, space reduction mechanisms and moreover a arcing classifier to aggregate the best classification results.

3.1.4. Proposed RBF-SVM Hybrid System

Given a set D, of d tuples, arcing [4] works as follows: For iteration i (i=1, 2,..., k), a training set D_i of d tuples is sampled with replacement from the original set of tuples D. some of the examples from the dataset D will occur more than once in the training dataset D_i. The examples that did not make it into the training dataset end up forming the test dataset. Then, a classifier model, M_i, is learned for each training examples d from training dataset D_i. A classifier model M_i is learned for each training set D_i. To classify an unknown tuple X each classifier M_i returns its class prediction, which counts as one vote. The hybrid classifier (RBF-SVM) M^* counts the votes and assigns the class with the most votes to X.

Algorithm 1: Hybrid RBF-SVM using arcing classifier.

Input:
D, a set of d tuples.
k=2, *the number of models in the ensemble.*
Base Classifiers (*RBF, SVM*)
Output: *Hybrid RBF-SVM model,* M^*.

Procedure:

1. *For i*=1 *to k do // Create k models.*
2. *Create a new training dataset,* D_i, *by sampling D with replacement. Same example from given dataset D may occur more than once in the training dataset* D_i.
3. *Use* D_i *to derive a model,* M_i.
4. *Classify each example d in training data* D_i *and initialized the weight,* W_i *for the model,* M_i, *based on the accuracies of percentage of correctly classified example in training data* D_i.
5. *endfor*

To use the hybrid model on a tuple, X:

1. *if classification then*
2. *let each of the k models classify X and return the majority vote.*
3. *if prediction then*
4. *let each of the k models predict a value for X and return the average predicted value.*

4. Performance Evaluation Measures

4.1. Cross Validation Technique

Cross-validation [18] sometimes called rotation estimation, is a technique for assessing how the results of a statistical analysis will generalize to an independent data set. It is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform in practice. 10-fold cross validation is commonly used. In stratified K-fold cross-validation, the folds are selected so that the mean response value is approximately equal in all the folds.

4.2. Criteria for Evaluation

The primary metric for evaluating classifier performance is classification Accuracy: The percentage of test samples that the ability of a given classifier to correctly predict the label of new or previously unseen data (i.e., tuples without class label information). Similarly, the accuracy of a predictor refers to how well a given predictor can guess the value of the predicted attribute for new or previously unseen data.

5. Experimental Results and Discussion

5.1. Dataset Description

The data used in classification is 10 % U.S. Zip code, which consists of selected records of the complete U.S. Zip code database. The database used to train and test the hybrid system consists of 4253 segmented numerals digitized from handwritten zip codes that appeared on U.S. mail passing through the Buffalo, NY post office. The digits were written by many different people, using a great variety of sizes, writing styles and instruments, with widely varying amounts of care.

5.2. Experiments and Analysis

The U.S. Zip codes dataset are taken to evaluate the proposed RBF-SVM handwriting recognition system using arcing (Algorithm1). All experiments have been performed using Intel Core 2 Duo 2.26 GHz processor with 2GB of RAM and weka software [29].

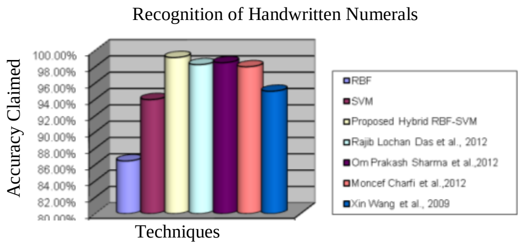

Figure 1. Classification accuracy.

The data set described in section 5 is being used to test the performance of base classifiers and hybrid classifier. Classification accuracy was evaluated using 10-fold cross validation. In the proposed approach, first the base classifiers RBF and SVM are constructed individually to obtain a very good generalization performance. Secondly, the ensemble of RBF and SVM is designed. In the ensemble approach, the final output is decided as follows: base classifier's output is given a weight (0-1 scale) depending on the generalization performance as given in Table 1. According to Table 1 and Figure 1, the proposed hybrid model shows significantly larger improvement of classification accuracy than the base classifiers and the results are found to be statistically significant.

Table 1. Experiments results.

Techniques	**Accuracy Claimed**
RBF	86.46 %
SVM	93.98 %
Proposed Hybrid RBF-SVM	**99.13 %**
Rajib *et al.* [9]	98.26 %
Om Prakash *et al.* [22]	98.50%
Moncef *et al.* [8]	98.00 %
Xin Wang *et al.* [28]	95.00 %

The results indicate that higher accuracy is achieved with the proposed hybrid RBF-SVM in comparison with prior work on the Handwritten Numerals. Most previous work has had accuracy in the 95-98% range [22, 29] while the performance was over 99% when using proposed hybrid RBF-SVM.

The x^2 statistic x^2 is determined for all the above approaches and their critical value is found to be less than 0.455. Hence, corresponding probability is $p< 0.5$. This is smaller than the conventionally accepted significance level of 0.05 or 5%. Thus examining a x^2 significance table, it is found that this value is significant with a degree of freedom of 1. In general, the result of x^2 statistic analysis shows that the proposed classifiers are significant at $p< 0.05$ than the existing classifiers.

The experimental results show that proposed ensemble of RBF and SVM is superior to individual approaches for handwriting recognition problem in terms of classification accuracy.

6. Conclusions

In this research, some new techniques have been investigated for handwriting recognition and their performance is evaluated based on the U.S. Zip code dataset to approximately 10% of its original size and then classifying the reduced data by RBF and SVM. RBF and SVM are explored as handwriting recognition models. Next a hybrid RBF-SVM model is designed using RBF and SVM models as base classifiers. Finally, a hybrid intelligent handwriting recognition system is proposed to make optimum use of the best performances delivered by the individual base classifiers and the hybrid approach. The hybrid RBF-SVM shows higher percentage of classification accuracy than the base classifiers.

The experiment results lead to the following observations.

- SVM exhibits better performance than RBF in the important respects of accuracy.
- Comparison between the individual classifier and the combined classifier: it is clear that the combined classifier shows the significant improvement over the single classifiers.

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