A SURVEY ON EVALUATING NEURAL NETWORK AND HIDDEN MARKOV MODEL CLASSIFIERS FOR HANDWRITING WORD RECOGNITION

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ABSTRACT
Handwritten recognition is of immense importance for processing of bank checks, postal address, forms, mail or technical document. The recognition by the machine is difficult due to high variability and uncertainty of human writing. Handwritten words are fairly complex in pattern, great variability in handwriting style and in the character shapes by individuals. Neural Network and Hidden Markov Model is base for many different types of applications in various fields, many of which we use in our daily lives. The widely used methods are Neural Networks (NN) and Hidden Markov Models (HMM). NN classifier is used to generate a score for each segmented character. HMM classifier is used to identify character in sequence of word with assigning a probability to each of them. The main objective of this paper is to study various methods of Neural Networks (NN) and Hidden Markov Models (HMM) classifier applied to the handwritten word recognition problem. Exploring the result obtained from individual classifier, merits, demerits and the tradeoff of both classifiers in improving the throughput of handwritten word recognition system.

KEYWORDS: *HMM, NN, Handwriting Style, Word Recognition Problem.*

I. INTRODUCTION

Handwriting is one of the most important ways in which civilized people communicate. It is used both for personal and business communications. Handwriting is the product of brain and hand, mind and body – thoughts expressed on paper using the muscles of the arm and hand, physical movements controlled by the brain. Handwriting recognition is the ability of a computer to receive and interpret handwritten input from sources such as paper documents, photographs, touch-screens etc. The Handwriting word recognition problem is concern with artificial intelligence, social issues, Authentication of documents etc. Handwritten word recognition is a complex and important problem. Recognition of handwritten word is important for automatic document processing. Recognition of handwritten word by computer pose serious problems because of the high variability in the character shapes by individuals. [3, 12]

The recognition of handwritten words by computers is a challenging task [25]. Despite the impressive progress achieved during the last years and the increasing power of computers, the performance of the handwriting recognition systems is still far from human performance. Words are fairly complex patterns and owing to the great variability in handwriting style, handwritten word recognition is a difficult one. The first sort of difficulties is due to the high variability and uncertainty of human writing. Not only because of the great variety in the shape of characters, but also because of the overlapping and the interconnection of the neighboring characters. In handwriting we may observe either isolated letters such as hand printed characters, groups of connected letters, i.e. sub–words, or entirely connected words. Furthermore, when observed in isolation, characters are often ambiguous

and require context to minimize the classification errors. Broadly the handwritten recognition systems are classified as Online Handwriting Recognition and Offline Handwriting Recognition.[8,21]

1.1 Online Handwriting Recognition

On-line handwriting recognition involves the automatic conversion of text as it is written on a special digitizer or PDA, where a sensor picks up the pen-tip movements as well as pen-up/pen-down switching. That kind of data is known as digital ink and can be regarded as a dynamic representation of handwriting. The obtained signal is converted into letter codes which are usable within computer and text-processing applications.[8]

1.2 Offline Handwriting Recognition

Offline handwriting recognition involves the automatic conversion of text in an image into letter codes which are usable within computer and text-processing applications. The data obtained by this form is regarded as a static representation of handwriting. The technology is successfully used by businesses which process lots of handwritten documents, like insurance companies. The quality of recognition can be substantially increased by structuring the document (by using forms).This work is mainly confined HMM and Neural Network.[8, 21].In section 2 related literature survey is discussed. In section 3 performance parameters, conclusion and future work is discussed respectively.

II. RELATED LITERATURE SURVEY

Lawrence [1] describes review of theoretical aspect of HMM as a statistical modeling and show how they are applied to selected problems in machine recognition of speech. In this paper he attempted to present the theory of hidden Markov models from the simple concept of discrete Markov chain. He also attempted to illustrate some applications of the theory of HMMs to simple problems in speech recognition and pointed out how the techniques have been applied to more advanced speech recognition problem. Yacoubi et al[2] describes a hidden Markov model-based approach designed to recognize off-line constrained handwritten words for large vocabularies. The word model is made up of the concatenation of appropriate letter models consisting of elementary HMMs and an HMM-based interpolation technique is used to optimally combine the two feature sets. Experiments carried out on real-life data show that the proposed approach can be successfully used for handwritten word recognition. Tay et al [3] describes an approach to combine neural network (NN) and Hidden Markov models (HMM) for solving handwritten word recognition problem. To recognize a word, the NN computes the observation probabilities for each letter hypothesis in the segmentation graph. The HMMs then compute the likelihood for each word in the lexicon by summing the probabilities over all possible paths through the graph. They introduce the discriminant training to train the NN to recognize junk. They use three database namely IRONOFF, SRTP and AWS. Also show the superiority of the hybrid recognizer compared to out baseline recognizer, which is using discrete HMM. Finally, they show that the hybrid recognizer can be bootstrapped automatically from the discrete HMM recognizer, and significantly improve its recognition accuracy by going through several training stages.

JOSE et al [6] evaluates NN and HMM classifiers applied to the handwritten word recognition problem. The strategy proposed takes advantage of the different but complementary mechanisms of NN and HMM to obtain a more efficient hybrid classifier. This evaluation was made using NN and HMM schemes with similar feature sets, therefore the results are influenced mainly by the classifiers performance. The recognition rates obtained vary from 75.9% using the HMM classifier alone to 90.4% considering the NN and HMM combination. Koerich et al [7] they describe a hybrid recognition system that integrates hidden Markov models (HMM) with neural networks (NN) in a probabilistic framework. An NN classifier is used to generate a score for each segmented character and in the end, the scores from the HMM and the NN classifiers are combined to optimize performance. Experimental results show that for an 80,000–word vocabulary, the hybrid HMM/NN system improves by about 10% the word recognition rate over the HMM system alone.

Abdul Rahim et al [8] describes A more recent recognition method based on Support Vector Machine (SVM) has been suggested as an alternative to NN. In speech recognition (SR), SVM has been successfully used in the context of a hybrid SVM/HMM system. It gives a better recognition result

compared to the system based on hybrid NN/HMM. It mainly compares NN and SVM in a word recognition system based on character level discriminant training. SVM have been shown to be a better character recognizer but drawback is a larger model size. Due to SVM's better discrimination capability, word recognition rate for SVM/HMM system will be better than in a NN/HMM hybrid system.Md. Rafiul and Nath [10] Hidden Markov Models (HMM) approach for forecasting stock price for interrelated markets. The results show potential of using HMM for time series prediction. Mohit Mehta et al [11] describes a unique technique of using HMM as feature rather than a classifier as being widely proposed by most of the authors in signature recognition. Results show a higher false rejection than false acceptance rate. Character segmentation accuracy is found to be 95%, character recognition efficiency 83%, Digit recognition efficiency is 91%.and system detects forgeries with an accuracy of 80% and can detect the signatures with 91% accuracy. Cheng-Lin Liu and Fujisawa describes the characteristics of the classification methods that have been successfully applied to character recognition, and show the remaining problems that can be potentially solved by learning methods. A. Senior [21] describes the design of a system that can transcribe handwritten documents. Three probability estimation techniques are described and their application to handwriting recognition investigated. The system tested on a database of transcripts from a corpus of modern English and recognition results are shown. John A. Fitzgerald et al[25] presents an innovative hybrid approach for online recognition of handwritten symbols. They propose new recurrent neural network architecture, associated with an efficient learning algorithm derived from the gradient descent method. They have used a rule-based approach for feature extraction only, thus avoiding the aforementioned disadvantages of such methods, as fuzzy rules need only be written for a limited number of feature types and properties. The features sets extracted are robust, and capture what is distinctive about each symbol, making classification easier for the network. Also, using these feature sets as input is more efficient than using the raw symbol data. Using the network for classification is a far more extendable approach than using fuzzy classification rules. They describe the network and explain the relationship between the network and the Markov chains.[25]

Once a system can be described as a HMM, three problems can be solved. The first two are pattern recognition problems: Finding the probability of an observed sequence given a HMM (evaluation); and finding the sequence of hidden states that most probably generated an observed sequence (decoding). The third problem is generating a HMM given a sequence of observations (learning).[1]

Problem 1. Evaluation

Consider the problem where we have a number of HMMs (that is, a set of (∏,A,B) triples) describing different systems, and a sequence of observations. We may want to know which HMM most probably generated the given sequence.

Use the forward algorithm to calculate the probability of an observation sequence given a particular HMM, and hence choose the most probable HMM.

This type of problem occurs in speech recognition where a large number of Markov models will be used, each one modeling a particular word. An observation sequence is formed from a spoken word, and this word is recognized by identifying the most probable HMM for the observations.

Problem 2. Decoding

Finding the most probable sequence of hidden states given some observations. Another related problem, and the one usually of most interest, is to find the hidden states that generated the observed output. In many cases we are interested in the hidden states of the model since they represent something of value that is not directly observable. They use the Viterbi algorithm to determine the most probable sequence of hidden states given a sequence of observations and a HMM. [1,18]

Problem 3. Learning

Generating a HMM from a sequence of observations. The third, and much the hardest, problem associated with HMMs is to take a sequence of observations (from a known set), known to represent a set of hidden states, and fit the most probable HMM; that is, determine the (π,A,B) triple that most probably describes what is seen. The forward-backward algorithm is of use when the matrices A and B are not directly (empirically) measurable, as is very often the case in real applications. Furthermore, the conditional– independence imposed by the Markov Model (each observation is independent of its

neighbors) prevents an HMM from taking full advantage of the correlation that exists among the observations of a single character [24].

The majority of recognizers for handwritten symbols have been built upon rule based methods or statistical methods, such as motor model, elastic matching, time-delay neural network, and hidden Markov models. The problem with rule based methods is that it is in most cases impossible to design an exhaustive set of rules that model all possible ways of forming all symbols. Solution on this is suggested in neural networks and most of the research refers Multi-Layer Perceptron (MLP) with Error Back Propagation Training (EBPT) algorithm. An MLP is a network of simple *neurons* called *perceptrons*. The basic concept of a single perceptron was introduced by Rosenblatt in 1958. The perceptron computes a single *output* from multiple real-valued *inputs* by forming a linear combination according to its input *weights* and then possibly putting the output through some nonlinear activation function. No matter what activation function is used, the perceptron is only able to represent an oriented ridge-like function. The perceptrons can, however, be used as building blocks of a larger, much more practical structure. A typical *multilayer* perceptron (MLP) network consists of a set of source nodes forming the *input layer*, one or more *hidden layers* of computation nodes, and an *output layer* of nodes. The input signal propagates through the network layer-by-layer [15].

Time-delay neural network (TDNN) trained with Back-propagation algorithm requires the setting of less parameters. The limitation of TDNN is that the input fixed time window can render it unable to deal with varying length sequence. Another type of network is the recurrent neural network, which successfully deal with temporal sequences such as formal language learning problems [25].

III. PERFORMANCE PARAMETER

The important point to note here is that all models, methods, neural networks etc. proposed for handwritten word recognition are highly depend for their results on features extracted from database images. Stronger the volume of available sample data, better the results. So all algorithms are relaying highly on feature extraction section for optimum output.

Transforming the input data into the set of features is called *features extraction* [14]. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Best results are achieved when an expert constructs a set of application-dependent features.

Another dependency for results is observed on segmentation methods used. In computer vision, segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image. Several general-purpose algorithms and techniques have been developed for image segmentation. Since there is no general solution to the image segmentation problem, these techniques often have to be combined with domain knowledge in order to effectively solve an image segmentation problem [14].

- Clustering methods
- Histogram-based methods
- Edge detection methods
- Region growing methods
- Level set methods
- Graph partitioning methods

- Watershed transformation
- Model based segmentation
- Multi-scale segmentation
- Semi-automatic segmentation
- Neural networks segmentation

IV. CONCLUSION

The method, using both NN and HMM, gives a simple scheme to identify individual character and to form best sequence. The key of system is its simplicity. It is very simple logic which just tries to combine the goodness of two independent classifiers. If the HMM is trained for any symbols in any language, it can recognize the proper sequence (word).But there are some limitations also, main is the rigid structure of HMM and its dependency on the history data. Less past data cannot give more options to system for deciding output. There may be some perfect answer which cannot be guessed by HMM, just because it is not in history or rarely applied in history, NN classifier does not guess at all. It just generates the answer for what it is trained for. With reference to various research works, NN is found to work well on word recognition system.

V. FUTURE WORK

The system can be used in various applications and for many languages, so our next work will to train the HMM's for those symbols. We can obtain better results if size of history data is increased and proper segmentation technique is used.

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