NEURAL NETWORK IN HANDWRITTEN RECOGNITION SYSTEM: A SURVEY

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ABSTRACT

Neural network is a branch of Artificial Intelligence that imitates the biological processing function of the brain. Neural network has been implemented in various applications. One of the applications is handwritten recognition system. Handwritten is the art of an individual, which is controlled by the function of the brain. Every individual has his or her own style of writing. Hence, reading the handwriting is sometimes quite difficult. Many researches have been done in this area and yet still continuing. This paper presents a survey on the application of neural networks in handwritten recognition system. Several methodologies including feature extractions, neural network models and algorithms are highlighted.

1.0 INTRODUCTION

Artificial Intelligence (AI) is a branch of computer science that is concerned with the automation of intelligent behavior (Luger, 2002). AI grew into numbers of branches including neural network (NN), fuzzy logic, expert system, etc. NN has been motivated from a study on human brain. Hykin (1999) describes brain as a highly complex, nonlinear, and parallel computer. Hence, the brain is capable to perform highly complex and computational tasks such as pattern recognition, perception and motor control. NN imitates these capabilities into an artificial neuron that comprises large number of computational processing elements called units, nodes or cells. Neuron are connected to each other with an associated weight that represents information (or knowledge) being used by the network to solve a problem.

The potentials of NN has attracted many researchers to develop and integrate NN in their applications. One of the areas of interest is handwritten recognition. Handwriting is a series of complex actions that involves human nerve system, physical, emotion and natural behavior (Kuner & Miedbrodt, 1999). The innovation of input devices such as digitizer, enable the computer to capture the handwriting while it is being applied on a paper. This approach is called online method. It can also be converted into a digital form using scanner or any OCR (Optical Character Recognition) devices. The later approach is classified as offline method.

Literature on this topic is extremely huge, with a variety of domains ranged from text to signature. Some of the literatures includes handwriting word recognition (Grob, 1997), handwriting signature verification (Murshed *et al.*, 1997), bank cheque recognition (Wahap *et al.*, 2002), car plate recognition (Husin *et al.*, 2002) and handwriting as a computer interface (Guyon & Warwick, 1995). Lazim *et al.* (1990) expressed that the main focus of handwritten recognition is to develop a new recognition technique that can be applied in all handwritings without any constraint. Currently, many studies have achieved the goal, yet many other challenges arise such as to improve the recognition rate, to improve the feature extraction algorithm and etc. In other word, more researches being done, more challenges would arise!

This paper aims to review the application of NN in handwritten recognition. It is organized as follows: Section 2 gives a description on handwritten recognition system; Section 3 explains the NN in handwriting application and summarizes its architecture. This follows by section 4 that describes the feature extractions techniques, and finally the conclusions.

2.0 HANDWRITTEN RECOGNITION SYSTEM

Handwriting recognition can be divided into two main types (Figure 1); i.e. text and signature recognition (Figure 2). Text can further be divided into three types; i.e. digit or number (Figure 3), character (Figure 4) and word recognition (Figure 5). Typically, there are five styles of handwriting namely, boxed discrete character, spaced discrete characters, run-on discretely written characters, pure cursive script writing and mixed cursive and discrete (Figure 6). In a study of handwritten courtesy amounts recognition of Malaysian bank cheques, Sulaiman & Khalid (2001) categorized the handwriting styles into four categories, namely, simple or single digit, connected digits, touched/ partial overlapped and full overlapped.

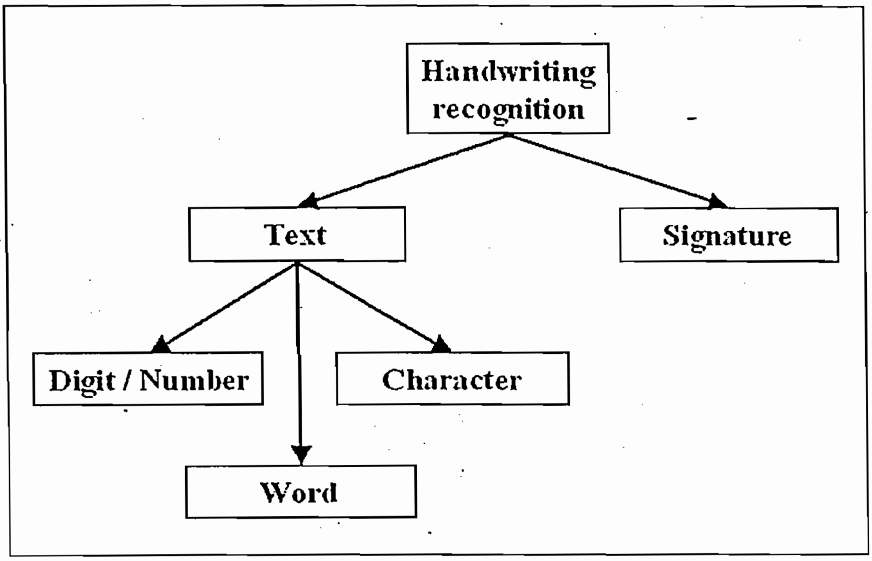

Figure 1: Types of handwriting recognition

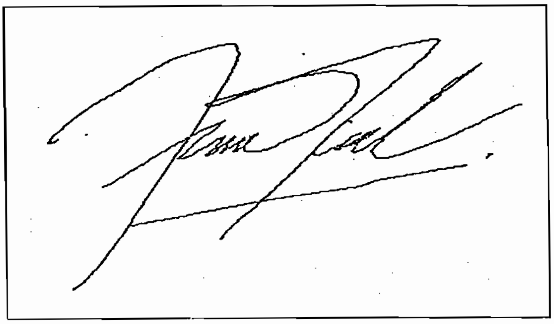

Figure 2: Example of Signature

Figure 3: Example of digit "2"

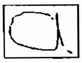

Figure 4: Example of character "a"

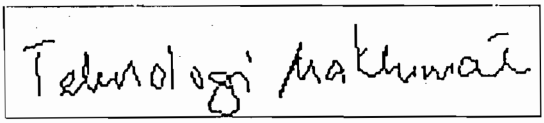

Figure 5: Example of word "Teknologi Maklumat"

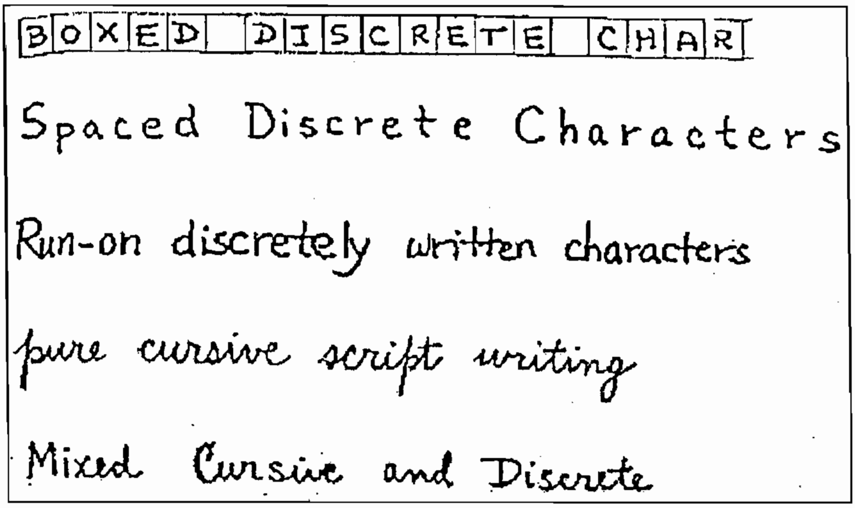

Figure 6: Categories of handwriting style

As discussed earlier, both text and signature recognition system can be either online or offline (Impedovo *et al.*, 1991; Seiler *et al.*, 1994). The division is based on how the system receives the data. Online system receives data directly from some sort of pen devices that attached to the computer. Whereas, for offline system, handwriting is already presented on a paper. Reading the handwriting will require some sort of reading devices such as scanner in order to transform the picture into a digital format. Both online and offline methods have give a significance interest to researchers, even though online input is sometime preferable (Seiler *et al.*, 1994; Powalka *et al.*, 1994). The difference between online and offline is summarized in Table 1.

Table 1: Online versus Offline (Sieler *et al.*, 1994)

	Online	**Offline**
Applications	Less Applications	Wider applications
Data	Pen trajectory	Pixel data
Input Devices	Writing Device	Scanner

A survey by Leclerc & Plamondon (1994) indicates that, offline signature verification has always been considered more difficult approach and gives worse results when it is compared to online. However, they also found that the approach has gain a great deal of interest to the scientific community. It gives a high financial impact especially on automated verification in cheques signature and signatures on official documents. Online signature verification is less difficult since the dynamic information of signature is available and easily captured. However, too much information caused constraint in choosing the best features to represent the signature.

3.0 NEURAL NETWORK IN HANDWRITING APPLICATIONS

Neural network alongside with statistical approach have been applied in numerous pattern recognition domain. Both approaches have numbers of advantages over the problem domain. However, these approaches are considerably overlapped (Sarle, 1994). In some studies, NN has outperformed the statistical approach while in some other studies statistical approach has outperformed NN approach. These achievements show that both approaches are strong and highly reliable in certain problem domains. Although NN limits itself with its black-box processing, but still NN is a promising alternative approach to explore.

NN plays an important role in handwriting applications. In handwritten signature application for example, NN is now used in signature segmentation, static (offline) and dynamic (online) signature verification (Leclerc & Plamondon, 1994). According to Leclerc & Plamondon, the advantages of NN is that it can be trained to recognize signatures and their characteristics, such as to classify genuine or forged signature as a function of time through a retraining process based on recent signatures.

Wahap *et al.* (2002) discussed a NN based bank cheque recognition system for Malaysian cheques. They uses backpropagation Multi Layer Perceptron (MLP) NN to recognize the numerical characters. The recognition results were only 72%. The low recognition is caused by feature extraction algorithms, which leads to wrong recognition. In a previous study by Sulaiman & Khalid (2001), they employed three layers of NN powered by backpropagation learning algorithm to recognize cursive handwritten amounts of Malaysian bank cheques. The study yields a promising recognition result up to 92% recognition rate with small percentage of unsuccessful recognition and fast convergence rates.

Another attempts is as recognition engine for car plate recognition (Al-Jumaily *et al.*, 2002). The recognizer is a multi layers feedforward NN and the approach yields encouraging results. Another study in similar domain by Husin *et al.* (2002) used MLP that was trained using backpropagation algorithm to recognize the car plate. The prototype called VISIONPLATEII yields encouraging results too.

Another version of TDNN called Multi-State Time Delay Neural Network (MS-TDNN). MS-TDNN combines the high accuracy pattern recognition capabilities of a TDNN with dynamic time warping algorithm (DTW) in order to find an optimal alignment between stroke and characters in handwritten words. Manke & Bodenhausen (1994) used MS-TDNN in training and testing for both cursive handwriting and single character recognition tasks. The recognition rates for cursive handwriting is more than 80% while single character is more than 90%. MS-TDNN also can be used to perform run-on recognition (Grob, 1997). Grob reported that even though the system was trained with some limitation, the result is very encouraging. Bengio & LeCun (1994) and Bengio *et al.* (1995) employed Multi-Layer Convolutional Neural Network (MCLNN) trained with a variation of BP algorithm in handwritten word recognition system. The system deals with all styles of handwriting. MCLNN was combined with HMM to achieve more accurate results and achieves large reduction in error rates.

MLP, TDNN, MS-TDNN and MCLNN are examples of NN models employed in handwritten recognition system. There are many other NN models and algorithms have been explored and employed in this domain such as Self-Organizing Map (SOM), Quickpropagation, Radial Basis Function (RBF), Recurrent Neural Network (RNN), Fuzzy ARTMAP, and etc. Some of the studies are summarized in Table 2.

Table 2: Neural Network Model and Architecture

Study	Types of handwriting	Source of Data	NN Model	Role	Applications
(Dodel & Shinghal, 1997)	Cursive Word	Offline	Quickpropagation	Recognizer	Read unconstrained handwritten worded amounts in bankchecks
			Backpropagation (BP)		
(Mighell *et al.*, 1989)	Signature	Offline	Backpropagation (BP)	Recognizer	Detecting forgery signature
(Cardot *et al.*, 1994)	Signature	Offline	Backpropagation (BP)	Decision network	Working on checks
			Multilayer Network	Intermediate processor	

			Kohonen Map	Classify the input	
(Schomaker *et al.*, 1993; Schomaker *et al.*,1994)	Cursive word	Online	Self Organizing Map (SOM)	Feature Quantizer	Handwriting Recognition System
(Vuori, 2002)	Any kind of writing style	Online		Cluster	Clustering Handwriting Style
(Bengio & LeCun, 1994; Bengio *et al.*, 1995)	All style of handwriting	Online	Multi-Layer Convolutional Neural Network (MCLNN)	Recognizer	Handwritten Word Recognition System
(Al-Jumaily *et al.*, 2002)	Digit / Number	Offline	Multilayer Perceptron (MLP) trained with Backpropagation Algorithm	Recognizer	Car Plate Recognition System
(Husin, *et al.*, 2002)	Digit / Number	Offline		Recognizer	VISIONPLATE II: License Plate Recognition System
(Janahiraman *et al.*, 2002)	Digit / Character	Offline		Recognizer	-
(Wahap *et al.*, 2002)	Digit / Number	Offline		Recognizer	Automated Cheques Processing
(Lemarie *et al.*, 1996)	Cursive Word	Offline	Radial Basis Function (RBF)	Estimation of emission probabilities	Handwritten Word Recognition System
(Senior, 1994)	Cursive word	Offline	Recurrent Neural Network (RNN)	Recognizer	Handwriting Recognition
(Schenkel *et al.*, 1995)	Cursive Word	Online	Time Delay Neural Network (TDNN)	Estimate a posteriori probabilities for characters in a word	Writer Independent System for on-line Handwriting Recognition
(Guyon *et al.*, 1995)	Isolated character, word and signature	Online		Feature extractor and classifier	Handwritten Cursive Word Recognition System
(Grob, 1997)	Any kind of writing style	Online	Multi-State Time Delay Neural Network (MS-TDNN)	Recognizer	Run-on Online Handwriting Recognition
(Manke & Bodenhausen, 1994)	Cursive Word	Online		Recognizer	Online handwriting Recognition

(Murshed *et al.*, 1997)	Signature	Offline	Fuzzy ARTMAP	Decision Network	Signature Verification for identifying random forgeries
(Sulaiman & Khalid, 2001)	Cursive Word	Offline	NN trained with Backpropagation Algorithm	Recognizer	Recognition amounts of Malaysian bank cheques

4.0 FEATURE EXTRACTION TECHNIQUES

Feature extraction is one of the vital components and major subproblem in most forms of pattern recognition since it involves determining the optimal feature set to extract from the raw data and how to compare those features. The feature set for handwriting is extremely large and can involve anything from pen-tip pressure and velocity to the position and duration of pen lifts and the number of minima and maxima in the x and y directions. Generally, any handwritten recognition methodology consists of data acquisition, preprocessing, feature extraction, comparison process, and performance evaluation. From the process of feature extraction, parameters are generated and become the input to the recognizer.

The process of feature extraction is differ due to the offline and online approaches. The feature extraction techniques in offline approaches shall be in one of the following form; 1) global features, 2) statistical features and 3) geometrical and topological features (Lee. *et al.*, 1992). In the first method, every pixel that lies within a rectangle or a frame is extracted. However, such features does not reflect any local, geometrical, or topological properties which is easily extractable and insensitive to noise. They are dependent upon position alignment and are highly sensitive to distortion and style variations. In statistical methods, features are derived from the statistical distribution of pixels of signature. According to Lee, the second method does takes some topological and dynamic information into account and can tolerate minor distorting and style variations but the third method is the most preferable. This is because it preserves the signature's global and local properties. In addition, high tolerance to distortion and style variations, and can also tolerate a certain degree of translation and rotation variations.

Janahiraman *et al.* (2002) combined geometrical and topological feature techniques on binary images to classify handwritten digits. Their studies has managed to produce relatively high recognition rate while reducing the input dimensionality. The same technique was applied in a recognition system for Malaysian cheques (Wahap *et al.*. 2002). In another study by Ramesh & Murty (1999), four different types of pattern representation schemes have been implemented namely geometric features, moment-based representation, envelope characteristics and tree-structured wavelet features.

Typically, the online approach captures data based on pen-up, pen-down, pen-move and speed. Gupta & Joyce (1997) describe a simple dynamic signature verification namely: total signature time, number of sign changes in the x and y velocities and the x and y accelerations, pen-up time and the total path length. The advantages of using just seven features is that comparison between genuine and test signatures are quite quick and efficient, and the values of the authentication features may be stored using only a very small amount of memory. The technique adopted by Gupta & Joyce has performed quite well in test and lead to a false rejection rate (FRR) of about half-a-percent with a false acceptance rate (FAR) of just over 10 percent. The same features are also employed by Dullink *et al.* (1997) in implementing their system. In a model by Singer & Tishby (1994), online handwriting is considered as a modulation of a simple cycloidal pen motion, describe by two coupled oscillations with a constant linear drift along the line of the writing. These parameters are then quantized into a small number of values without altering the writing intelligibility.

5.0 CONCLUSION

Handwriting is a special art of human being which has influenced innovation of today's technologies. Many pen-based systems such as PDA (Personal Digital Assistance) have been developed. Users enter the input by writing on the screen and the system will capture and recognize the character. Recognizing single character could be easy. However, when dealing with cursive and mixed cursive word, the recognition could be difficult and challenging tasks.

Many approaches have been invented to recognize the handwriting and one of them is NN. NN which is motivated by human learning capability (the brain function) is a promising and potentials approach in recognizing handwritten words and characters. Studies have shown that NN can perform very well and yields encouraging results. In some problem, NN could be combined with other approaches such as statistics or even with other NN models to produce better results. In a nutshell, more researches on NN particularly in handwritten recognition domain should be continued since it is a promising and potentials technology to explore.

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