TEST Engineering & Management

January-February 2020
ISSN: 0193-4120 Page No. 15750 - 15756

Effect of Neural Network Generalization on the Online Handwritten Patterns

[1]Ramya S, [2] Kumara Shama
[1] Manipal Institute of Technology, E & C Department, Manipal, India,
[2]Manipal Institute of Technology, E & C Department, Manipal, India

Article Info
Volume 82
Page Number: 15750 - 15756
Publication Issue:
January-February 2020

Article History
***Article Received**: 18 May 2019*
***Revised**: 14 July 2019*
***Accepted**: 22 December 2019*
***Publication**: 28 February 2020*

Abstract:
The work focusses on the recent trends on pen computing applications. Online handwritten patterns are acquired using pen tablets. In Online handwritten systems, data is acquired during the writing, which provides the dynamic movements of the pen trajectory with the time. The acquired online patterns are preprocessed, and angular information for the successive points are extracted. These features are input to the Feed Forward Neural Network model. Supervised Learning methods are implemented, and the performance of the system is evaluated for the generalization capability of the Neural Network on the online handwritten patterns. The selected patterns are vertical, horizontal and with various angular strokes. The evaluation results demonstrate the robustness of Neural Network for online pen strokes. The Neural network exhibits significant generalization for unseen, a new set of data.

***Keywords**: Generalization, Online Handwritten Patterns, Artificial Neural Network.*

I. INTRODUCTION

Traditionally, man-machine communication has been based on keyboard and pointing devices. With the development of faster computers, it is a need to build a most convenient man-machine interface which can be used for writing, drawing, click on a button, even for playing a game. Thus pen-based interfaces are becoming progressively prevalent [1] which enables intuitive handwriting based text input for end-users with the advantages of being comfortable, friendly, and natural way of interacting with a computer.

The challenge with the pen-enabled device is to identify user handwritings. Handwriting is the more attractive and natural form of input method. Handwriting Recognition (HR) is classified into offline handwriting recognition, also known as Optical character recognition (OCR) and Online Handwriting Recognition (OHR). In offline systems, recognition takes place on a static image captured once the writing procedure is over. In On-line systems, handwriting information is collected during the writing process, which provides pen trajectory information. Pen Tablet consists of digitizer and pen, which is known as a stylus. The digitizer detects the pen movement. The pen movement is a function of horizontal (x), vertical (y) coordinates and time. A sequence of samples between pen-down and pen-up is known as a stroke. These pen movements can be stored in the form of digital ink, which contains the dynamic representation of handwriting. The main advantage of on-line handwriting data over offline is the dynamic information of writing processes such as the writing acceleration, speed and its pressure against the writing surface area in the form of strokes.

Artificial Neural Network (ANN) is used in most of the pattern recognition field [3]. ANN is an enormously parallel distributed processor made up of simple processing units known as Neurons. Neuron stores experiential information in the form of weights [4]. ANN exhibits characteristics like Learning, Pattern Completion, Generalization, Fault Tolerance and Clustering.

Online Handwriting Recognition involves the recognition of stroke patterns. Unconstrained handwriting recognition exhibits handwriting style

January-February 2020
ISSN: 0193-4120 Page No. 15750 - 15756

variations. These variations are geometrical. The common geometrical properties are size, position, an aspect ratio of strokes, retraces, slant of strokes and number of strokes. This is a challenging computational problem mainly due to the vast differences associated with the stroke patterns. So online stroke identification is a crucial step in OHR. The recognition performance depends upon signal processing steps and recognition steps. In this research performance evaluation method to test the generalization capability of the neural network is developed for the feed-forward neural network model. The literature review is provided in section II,. In section III, the proposed method is explained. The experimental implementation and results are dealt in section IV and V, respectively. Then finally conclusion is presented.

II. Literature Review

Automatic pattern identification (API) is one of the active areas of research for the past four decades. The machine recognition of handwritten information is difficult due to similarity in the shapes of different characters, script complexity and non-uniqueness in the representation of diacritics. Thus efforts are underway for the development of efficient OHR systems. In 1956 Rand Systems were introduced which supported for Online Handwriting Recognition (OHR). In 1964 Brown [5] reported OHR for English characters using stroke order based with a limited character set. These earlier systems were bulky and costly and far from reach of the common man. Various industries launched many new fast and efficient technologies in PDA by 1980s which renewed the OHR research. The challenge with the pen-enabled PC is to recognize user pen strokes [6]. Hussain et al. [7] in 2005 worked on online Urdu Ligature Recognition using Spatial-Temporal Neural Processing with 85% of accuracy. English online characters recognition is carried out using Backpropagation Neural Nets [8] with 87 % accuracy. They claim that they considered distorted characters. Based on Kohonen Neural Network, Kannada language recognition is implanted by Vishwas with 95% accuracy [9]. Yann [10] in 1994 recognized Word level based on convolutional Neural networks which use the Neural network and HMM-based recognition techniques. But the research related to the evaluation of neural network adaptation for variation in the input is not tested with online strokes. So work is carried out to explore the Neural Network for its generalization capability on pen strokes.

III. Proposed Methodology

The work is focused on evaluate the generalization capability of ANN on online handwritten pen stroke pattern database. Since there is no publicly available pen stroke database, we have built a stroke database. Since online strokes are very vast, work is tested for basic strokes, and it can be extended for other strokes. Neural Network techniques are selected because it mimics human identification capabilities. Following are our objectives

·To build online handwritten pattern database.

·To investigate dominant features in the pattern.

·To recognize online handwritten pattern using a neural network-based technique.

·To evaluate the generalization capability of neural network technique.

The proposed research is divided into three phases namely, Data acquisition, training and testing phase.

A. Data Acquisition Phase

Fig. 1 shows the schematic diagram of Data acquisition system. Raw data containing horizontal and vertical co-ordinates information along with the time are collected from the user using tablet digitizer.

Fig 1. Block diagram of Data acquisition

The pen patterns are stored in XML format which contains pen up and pen down information with file ID representing author, sample number.

January-February 2020
ISSN: 0193-4120 Page No. 15750 - 15756

B. *Training Phase*

The collected data are utilized for training the neural network, as shown in Fig. 2. Online handwritten patterns collected from the users are often noisy and inconsistent. Hence input patterns are pre-processed, and features are extracted. The ANN is trained with the extracted features to receive the correct classification.

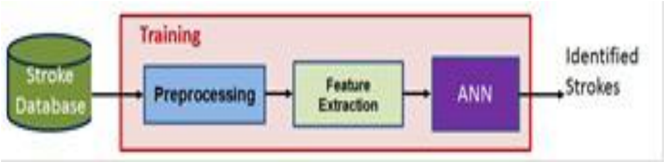

Fig. 2Block diagram of training procedure

C. *Testing Phase*

The test patterns are pre-processed, and features are extracted similar to the training phase. But in the testing phase, extracted features are input to the trained ANN models and evaluated for its capabilities as depicted in Fig. 3.

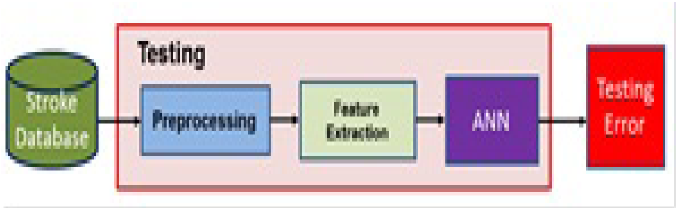

Fig 3. Block diagram of testing procedure

IV. Implementation

On-line handwritten patterns are collected using Pen Tablet. For data collection, the GUI was developed using visual C#. The handwritten patterns are saved with horizontal (x) coordinates, vertical (y) coordinate and time (t) information in the XML standard. The proposed work focuses on the two basic strokes, namely vertical and horizontal stroke. The selected patterns for data collection are as shown in Fig. 4.

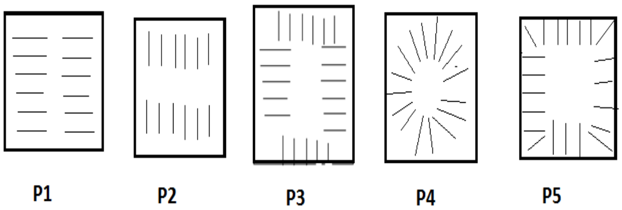

Figure 4. Pattern templates

Pattern P1 contains horizontal lines, P2 pattern contains vertical lines. P3 pattern contains horizontal and vertical strokes, whereas pattern P4 and P5 contains mixed type of lines. Data is collected from 10 users for 5 patterns. The experiment is repeated for 5 times by following Fishers method of data collection. Each pattern on average contains 12 strokes.So data samples of (12 x 10 users x 5 patterns) x 5 repetitions contributing 3000 data samples are collected. Among this 60% (P1+P2+P3) strokes are used for training the Neural Network and 40% (P4+P5) used for testing.

Fig. 5 shows the screen shot of sample online stroke saved in XML format and Table I gives the statistics of pen stroke data collection.

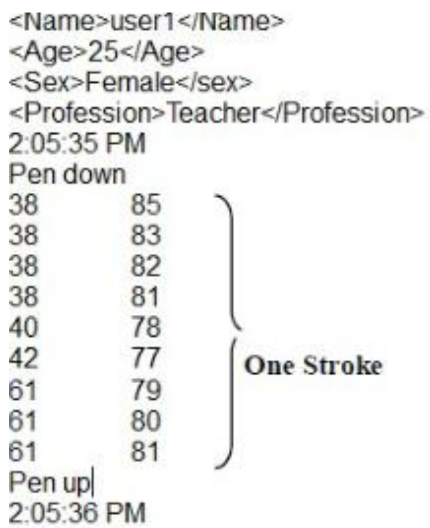

Fig. 5. Sample online stroke file

TABLE I. STATISTICS OF PEN STROKE DATABASE

Database size	3256 stroke samples
Training stroke samples (P1+P2+P3 patterns)	1858 stroke samples
Testing stroke samples (P4+P5 patterns)	1416 stroke samples
Maximum length of the stroke	68 points(x,y)
Minimum length of the stroke	34 points(x,y)
Observation	Number of Vertical strokes > Number of horizontal strokes

TEST Engineering & Management

January-February 2020
ISSN: 0193-4120 Page No. 15750 - 15756

A. Preprocessing

The raw pen patterns consists of the horizontal (x) and vertical (y) coordinates values corresponding to the pen trace. These pen patterns are subjected to noise removal, resampling and normalization. Noise removal [11] is carried out using moving average filter of window size three to remove repeated points. The noise removed data is resampled [12] in space by linear interpolation so that each pen patterns consists of 20 points. Let the smoothed and resampled pen pattern be represented by the sequence as in (1).

$$\mathrm{P}= [p1, p2, \ldots\ldots p20\,] \qquad (1)$$

where the vector pi = $(x_i\,;\,y_i)^T$ and x_i , y_i denote the horizontal and vertical coordinates. Then data are shifted and size normalized to get a new sequence as in (2).

$$Q = [q1, q2, \ldots\ldots q20\,]\,] \qquad (2)$$

where the vector qi = $(a_i; b_i)^T$ is given by (3),(4)

$$ai = (x_i - x_{min}\,)/(x_{max} - x_{min}\,) \qquad (3)$$

$$bi = (y_i - y_{min}\,)/(y_{max} - y_{min}\,) \qquad (4)$$

where, $(x_{min};\ y_{min})^T$ and $(x_{max};\ y_{max})^T$ denote the minimum and the maximum x and y coordinate values for the stroke under consideration.

B. Feature Extraction

Fig. 6 shows angular relationship θ of sample horizontal and vertical stroke with reference x axis. Horizontal stroke has 0° with respect to the reference line where as vertical line has 90°. This angular information distinguishes the two strokes. So tangent slope angle at point i for all x, y points are calculated using (5). We get 19 angular data from 20 resampled points, which has been used to train the Neural Network.

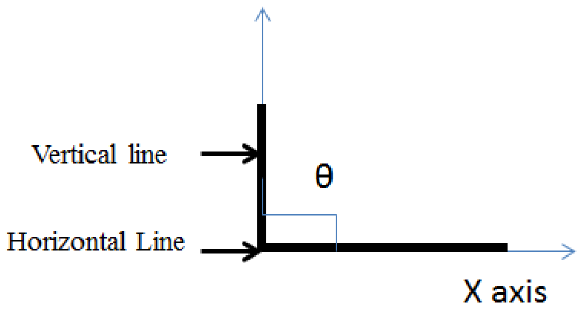

Figure 6. Angular relationship of horizontal and vertical stroke with reference X axis

$$\theta = tan^{-1}(y_{i+1} - y_i)/\ (x_{i+1} - x_i)(5)$$

C. Stroke Identification

Stroke identification is done using Artificial Neural Network(ANN).Since anular features are 19 and 2 strokes to be identified, an artificial neural network having 19 inputs and

2 outputs is created with 3 layer feed forward architecture as shown in Fig 7. Levenberg-Marquardt algorithm is used for training because it is fast and efficient.

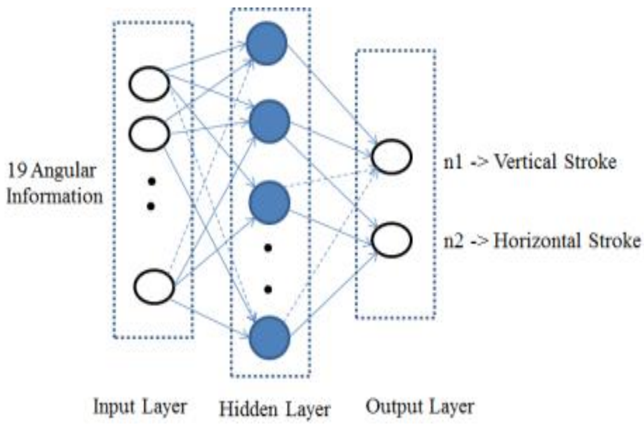

Fig. 7. Block diagram of ANN

V. Experimental Results And Discussions

A. Figures and Tables

Table II shows angular information obtained for a sample stroke. Fig. 8 shows training result of Neural Network. Neural Network is trained for 1858 stroke samples from Pattern P1, P2, P3 which contains horizontal and vertical strokes.

January-February 2020
ISSN: 0193-4120 Page No. 15750 - 15756

TABLE II. ANGULAR INFORMATION FOR A SAMPLE STROKE

Input online stroke	Feature Extraction (Angle between successive points)
	89.3104 89.2268 86.2445 76.2980 72.6197 88.1088 * * 90.001 (values are in degree wrt X axis)

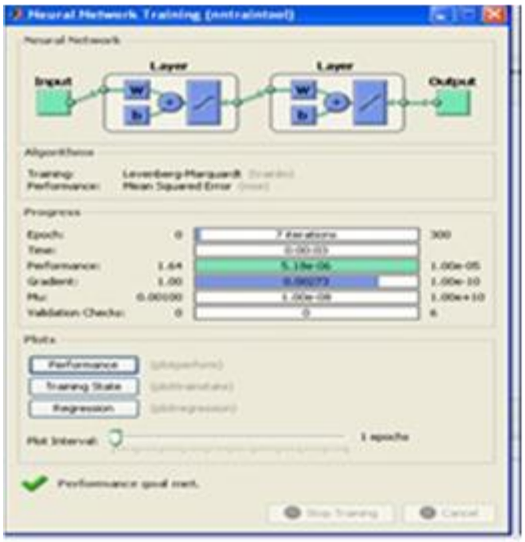

Fig. 8. Training result of neural network

Table III shows output of neural network. Based on the response of neural network neuron n1 and n2, a stroke code is built as shown in Table IV. We have tested the Neural Network for 1416 test samples from Pattern P4 and P5 which contains variation in horizontal and vertical lines.

TABLE III. RESPONSE OF NEURAL NETWORK

Neuron No	Response of Output Neuron	Trained for Stroke
n1	0.9988	Vertical Stroke
n2	0.0006	Horizontal Stroke

TABLE IV. STROKE CODE TABLE

No	Condition	Code	Stroke
1	n1>0.5 ,n2 < 0.5	10	Vertical Stroke
2	n1<0.5 ,n2> 0.5	01	Horizontal Stroke
3	n1<0.5 ,n2 < 0.5	00	Unknown
4	n1>0.5 ,n2 >0.5	11	Ambiguity

Fig. 9 shows the result of stroke identification.It is observed that identified Vertical strokes is more than identified Horizontal strokes. It is due to data for vertical strokes are more than horizontal strokes as discussed in section IV. 124 stroke samples out of 1416 test samples are identified as ambiguous (8%).48 out of 1416 samples (3 %) are unknown strokes.

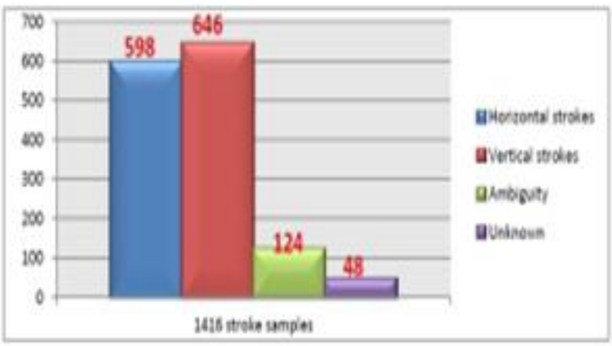

Fig. 9. Result of online stroke identification

Table V shows the result for some test samples. When the strokes are highly deformed, network is not able to recognize.

January-February 2020
ISSN: 0193-4120 Page No. 15750 - 15756

TABLE V RESULT OF ONLINE STROKE IDENTIFICATION

Sample stroke	Identified Stroke
	Horizontal Stroke
	Horizontal Stroke
	Horizontal Stroke
	Vertical Stroke
	Vertical Stroke
	Vertical Stroke
	Ambiguity
	Ambiguity
	Unknown
	Unknown

To test the ambiguity condition we have represented strokes an angular form as shown in Fig. 10. Line A represent horizontal line and line B represent vertical line.The stroke samples having variations of ±25° from horizontal line A are identified as horizontal stroke and ±25° from vertical directions are categorized as vertical stroke.It implies that Neural Network is able to adopt for ±25° variations in strokes.

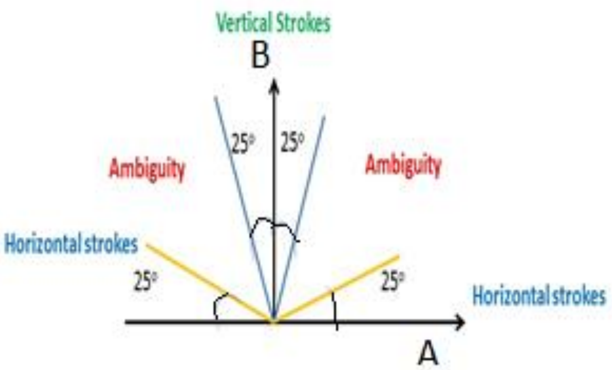

Figure 10 Identification regions in angular form

Test samples having high deformations are categorized as unknown strokes.The angular variations more than ±25° from horizontal and vertical directions are categorized as Ambiguous Strokes. but this Ambiguity state can be used to train 45°stroke.

CONCLUSION

An Artificial Neural network based system for the online pen stroke identification is developed and tested. The evaluation section proves the robustness Neural Network for online pen strokes. Thus neural network shows significant generalization for unseen, new set of data. Research can be extended for other stroke by using appropriate feature extraction and training methods. Ambiguity state can be used to train 45° stroke. This work can be incorporated for online handwriting recognition

REFERENCES

1. Nakagawa M., “Non-keyboard input of Japanese text-online recognition of handwritten characters as the most hopeful approach”, Information Processing, vol. 13, no.1, pp. 15-34, 1990.
2. Bahlmann C. and Burkhardt H., “The Writer Inependent On-line Handwriting Recognition System Frog on Hand and Cluster Generative Statistical Dynamic Time Warping”, IEEE transactions and Pattern Analysis and Machine Intelligence, vol.26, no.3. 2004
3. Amit Konar, Artificial Intelligence and Soft Computing, CRC Press LLC, United States of America,2000.
4. Nikola K. Kasabov, Foundations of Neural Networks,Fuzzy Systems, and Knowledge Engineering, The MIT Press, Cambridge, Massachusetts, London, England 1998.
5. Brown R. M., “On-line computer recognition of hand printed characters” , IEEE Trans, Electr. Comput., vol. EC-13, pp. 750-752,Dec. 1964.
6. Plamondon R. and Srihari S. N., “On-line and offline handwriting recognition: A comprehensive survey”. IEEE Trans. on PAMI, 22(1):6384, 2000.
7. HussainMasroor and M.N. Khan, “Online Urdu Ligature Recognition using Spatial Temporal

Neural Processing", In proceedings of INMIC, 2005.

8. Zafar Muhammad Faisal, DzulkifliMohamad and Muhammad Masood Anwar, "Recognition of Online Isolated Handwritten Characters by Backpropagation Neural Nets Using Sub-chracter Primitive features" in IEEE Int. Conf. on Neural Networks, NY,vol. 1, pp. 157-162, 2006.
9. Vishwaas M, Arjun M M and Dinesh R, " Handwritten Kannada Character Recognition based on Kohonen Neural Network" IEEE Trans. on PAMI,:91-97, 2012.
10. Yann Le Cun and YoshuaBengio, "Word Level Training of a Handwritten recognizer based on Convolutional neural Networks", ICPR Jerusalem Israel on Pattern recognition and Neural Networks,1994
11. Venkatesh N.M and Ramakrishnan A.G., "Choice of classifiers in Hierarchical Recognition of Online Handwritten Kannada and Tamil Aksharas", Universal Computer Science, vol. 17, no. 1 (2011), 94-106, 2011.
12. Deepu V., SriganeshMadhvanath, and Ramakrishnan A. G. , "Principal Component Analysis for Online Handwritten Character Recognition" , 17th IEEE International Conference on Pattern Recognition, pp.1051-4651/04