Aminu
Dutse Journal of Pure and Applied Sciences 1(2) December 2015 pp 93 – 96

CHARACTER RECOGNITION USING A GMDH TYPE NETWORK

Aminu Aliyu Abdullahi
Department of Computer Science, Federal University Dutse
aminu.abdullahi@study.beds.ac.uk, alamindelta1@yahoo.com

ABSTRACT
Creating an efficient system that can automatically recognize handwritten characters can be challenging, this becomes more apparent when the immense variability in human handwriting styles is taken in to account. The proficiency of character recognition systems also changes with changes in the script being used. The relatively decent recognition capacity of the human brain has motivated the use of artificial neural networks which attempt to mimic the processes of the brain at this task, but even such endeavors have fallen below the facility of the human brain at such tasks. The variability in writing styles from one individual to another has been cited as possible reasons behind this. This paper looks into using a GMDH like neural network for the recognition of human handwriting.
Keywords-: Hand Writing Recognition; Character Recognition; Artificial Neural Networks; Deep Neural Networks

INTRODUCTION

The variability of modern handwriting styles which differs on an individual basis has made complex the problem of handwriting recognition. (Pesch et al., 20112). Historically, this complexity has made t handwriting recognition an important testing ground from novel concepts in machine learning pattern recognition and feature selection (Deng, 2012). The unconstrained nature of the average day to day human handwriting scheme only adds to its complexity. According to Pesch, (2012) the high level of inter class variability means a substantial amount of computational resource has to be expended in statistical and other pre-processing steps.

According to Rehman and Saba 2014, a substantial number of handwriting recognition systems expend computational resources applying corrective measures such slant correction, line estimation etc. before the actual task of recognition and learning. These measures are in part due to the unordered nature of human handwritings.

To reduce recognition errors, systems have adopted radical pre-processing methodologies that attempt writing correction, orientation correction and re alignments. But these strategies can be computationally costly.

Although numerous machine learning strategies such as support vector machines, Markov model, convolutional neural networks and deep neural networks have been applied to the problem of handwriting recognition (Cheriet *et al.*, 2009; Kim and Bang, 2000; Mahmoud, 2008). GMDH based neural networks have some advantages when compared to other models; GMDH uses a simple polynomial model that slowly adds complexity to the final makeup of the model. Polynomial based models are recognised for their fast learning and dimensionality reduction properties especially when dealing with predictive models (El-Alfy, 2010)

This paper proposes a linear method of handwriting recognition that uses a modified version of the group method of data handling polynomial (GMDH) for recognition. The principal components extracted using PCA are used as raw inputs to the 3 layer network.

BACKGROUND

First proposed by Alexy Ivankhneko, GMDH is an inductive algorithm that uses a linear polynomial to compute a solution that is a subset of its primary function. The application of this polynomial strategy in artificial neural networks provided machine learning with one the earliest versions of deep learning in neural networks (Schmidhuber, 2015).

GMDH presents a self-generative strategy to machine learning. Models of learning are constructed using a regression technique as data flows through the multiple layers of an artificial network. A complex model can then be built using neural nets connected using a quadratic polynomial (Sheikholeslami *et al.*, 2014).

The inductive nature of GMDH based artificial neural networks has made them ideal for normative challenges which include the problem of handwritten character recognition. El-Alfy (2010) applied a hybrid GMDH neural network to the problem of handwritten numeral recognition. The system uses a predicted squared error criterion (PSE} for optimisation while fitting squared error (FSE) was used for training optimisation.

Other artificial neural network strategies have also been applied in the analysis of handwritten characters. Pan *et al*. (2015) proposed a discriminative convolutional neural network for handwritten digit recognition. The system used a cascade model between convolutional neural networks to implement discrimination as a basis for optimising network performance.

Zamora-Martinez *et al*. (2014) proposed a recurrent neural networks and a hidden markov model to construct a hybrid network for character recognition. The uses a language model that also uses syntactic structures to aid the performance of the network. These systems although optimal in performance expend a considerable amount of computational effort in pre-processing tasks which tend to increase the time taken for training and optimisation. The idea behind the proposed is to exploit the simplistic polynomial signatures of GMDH in order to construct network models that can compete with these other models in performance standards.

Proposed System

The novel aspect of the proposed system is a minute correction in the GMDH equation. Generally, a group method for data handling system uses a polynomial function Chauhan at al. (2014).

The proposed system employs diverse feature selection approaches as the inputs to the neural network. These features will therefore denote X_i in the GMDH equation. The first layer of the network will compute the performances of these different features and those with the best performances will then be selected for the subsequent layer of the network.

The proposed system employs a three layer approach with inputs being the various features selected using a feature selection method (e.g. PCA, ICA or LDA). The subsequent layers of the network then select the best features and compute a higher order output.

The original GMDH equation given by (Kalogirou, 2014):

$$\mathrm{Y} = \mathrm{G}(xi_i , x_j) = \mathrm{a}0 + \mathrm{a}1X_i + \mathrm{a}2\, X_j + \mathrm{a}3\, X_iX_j + \cdots \quad (1)$$

Is changed to:

$$\mathrm{Y} = \mathrm{G}(xi_i , x_j) = \mathrm{a}1X_i + \mathrm{a}2\, X_j + \mathrm{a}3\, X_iX_j + \ldots \quad (2)$$

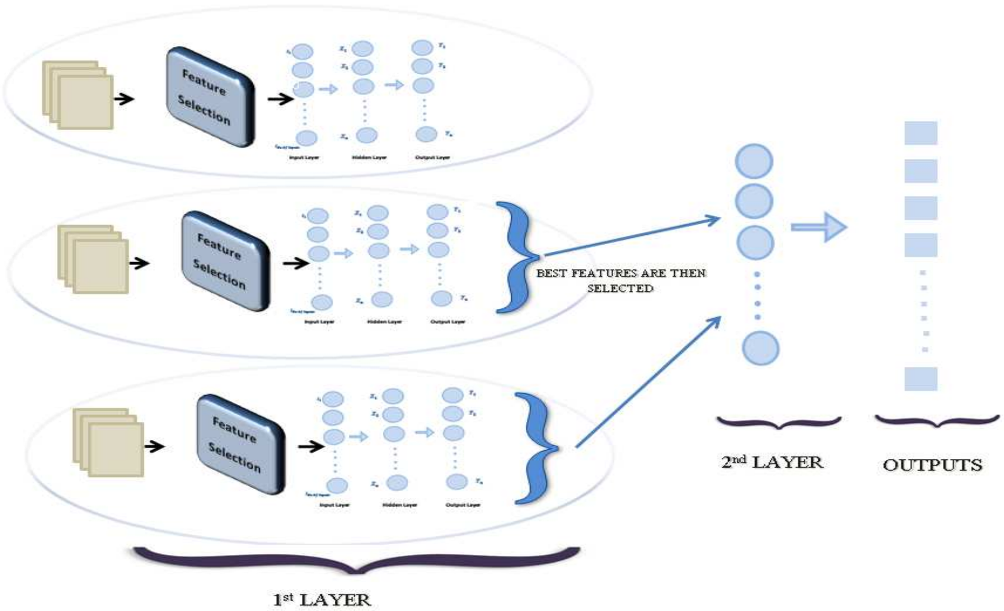

Figure 1, Structure of the Proposed System.

The novelty behind this apporach is that it may allow for easier covergence of the network by weighting the first coefficient in the polynomial.

The first layer composes of an input layer with fifty hidden neurons which sends their output to layer equal to the number of classes of the dataset. The networks with the best mean performance are then selected and their outputs forwarded to upper layers. The second and final processing layer is used to further tune and refine the outputs received from lower layers.

Recalling equation number (2),

$$Y = G(xi_i\ , x_j) = a1X_i + \ a2\ X_j + \ a3\ X_iX_j +$$

For every set of features X_i to X_j the neural network process these features as inputs with weights A_1 to A_n .with n being the number of feature sets selected, three (3) in our case.

The performance of the system is guided by:

$$Min_n \frac{1}{n} \sum_{i=1}^{n} l(f(X^i, W_1, \ldots\ldots W_n), Y^i) \quad (3)$$

Where l denoted the loss function which in this case is mean squared error.

Results and Discussion

The proposed system was tested on the MNIST database of handwritten digits. The dataset is a composite of 60,000 training images and 10000 test images.

The images are in a monochrome black and white format with which image stored in a 20X20 pixel setup.

Using Tansig as the activation function of the network and 100 principal components with hidden neurons, the system achieved a performance of **0.905**

```
5 0.914
Average: mp = 0.905, sp = 0.016
```

Reducing the no of principal components to 61 increases the performance to **0.928**

```
5 0.926
Average: mp = 0.928, sp = 0.005
```

This performance (of 92.8%) falls just shy of the highest recorded performance on the MNIST database (97%) (Yann.lecun.com, 2015).

Changing the feature selection method from Principal Components Analysis PCA to LDA resulted in a minor drop in the performance of the system to 0.92 while using Independent Component analysis resulted in a performance of 0.89.

Comparison

Tests on the MNIST database using Principal components analysis yielded an accuracy of **92%** placing it within the top contenders for maximal classification.

NN Type	Classification Method	Feature Selection/ Pre-processing Method	Error Rate
Proposed GMDH Type Network	GMDH Type Artificial Neural Network	PCA	7.2%
K-Nearest Neighbours (Keysers at al. , 2007)	K-Nearest Neighbours with non-linear deformation (P2DHMDM)	Shift able edges	48%
Proposed GMDH Type Network	GMDH Type Artificial Neural Network	LDA	8%
Proposed GMDH Type Network	GMDH Type Artificial Neural Network	ICA	11%
Deep Neural network	6-layer Artificial Neural Network 784-2500-2000-1500-1000-500-10	None	35%

A comparison with previously published systems indicates the optimality of the proposed system. The Error rate of 7.2% while using PCA for feature recognition is so far the best performance recorded with a GMDH type neural network system. The method of feature selection has also been shown to have a marginal impact on recognition performance.

FURTHER WORK

Further work will entail tweaking the parameters of the GMDH- type network in order to increase the efficiency of the system. Particular attention may also be directed towards building a normative model to assess the discrepancy in performance when feed forward structures are used with the same feature models.

REFERENCES

Chauhan, N., Sharma, M. & Singh, P. (2014) 'A Hybrid Approach towards Cost Effective Model for Handwritten Character Recognition', *International Journal of Computer Applications,* 95 (14), .

Cheriet, M., El Yacoubi, M., Fujisawa, H., Lopresti, D. & Lorette, G. (2009) 'Handwriting recognition research: Twenty years of achievement… and beyond', *Pattern Recognition,* 42 (12), pp.3131-3135.

Claudiu Ciresan, D., Meier, U., Gambardella, L.M. & Schmidhuber, J. (2010) 'Deep big simple neural nets excel on handwritten digit recognition', *ArXiv Preprint arXiv:1003.0358,* .

Deng, L. (2012) 'The MNIST database of handwritten digit images for machine learning research', *IEEE Signal Processing Magazine,* 29 (6), pp.141-142.

El-Alfy, E.M. (2010) *Neural Networks (IJCNN), The 2010 International Joint Conference on.* IEEE.

Keysers, D., Deselaers, T., Gollan, C. & Ney, H. (2007) 'Deformation Models for Image Recognition', *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* 29 (8), pp.1422-1435.

Kim, D. & Bang, S. (2000) 'A handwritten numeral character classification using tolerant rough set', *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* 22 (9), pp.923-937.

Mahmoud, S. (2008) *Innovations in Information Technology, 2008. IIT 2008. International Conference on.* IEEE.

Pan, S., Wang, Y., Liu, C. & Ding, X. (2015) *Machine Vision Applications (MVA), 2015 14th IAPR International Conference on.* IEEE.

Pesch, H., Hamdani, M., Forster, J. & Ney, H. (2012) *Frontiers in Handwriting Recognition (ICFHR), 2012 International Conference on.* IEEE.

Rehman, A. & Saba, T. (2014) 'Neural networks for document image preprocessing: state of the art', *Artificial Intelligence Review,* 42 (2), pp.253-273.

Schmidhuber, J. (2015) 'Deep learning in neural networks: An overview', *Neural Networks,* 61 pp.85-117.

Sheikholeslami, M., Sheykholeslami, F.B., Khoshhal, S., Mola-Abasia, H., Ganji, D. & Rokni, H.B. (2014) 'Effect of magnetic field on Cu-water nanofluid heat transfer using GMDH-type neural network', *Neural Computing and Applications,* 25 (1), pp.171-178.

Zamora-Martínez, F., Frinken, V., España-Boquera, S., Castro-Bleda, M.J., Fischer, A. & Bunke, H. (2014) 'Neural network language models for off-line handwriting recognition', *Pattern Recognition,* 47 (4), pp.1642-1652.