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Accuracy analysis in back propagation neural network considering neurons proportionality among hidden layers

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ABSTRACT

In this paper, an analysis is performed on the importance of proportionality among multiple hidden layers of BPNN. In case of any discrepancies in the network, a maximum of two layers is enough to train the whole neural network to get the desired result. But in some situations where accuracy is the chief criteria and training data is similar in data sets, (Like in Multiscript Numeral Recognition where shapes of different numerals resemble different values), in such conditions, accuracy matters the most. This paper describes a five-layer hidden approach to get the most possible accurate results in Multiscript Pin Code Recognition System using MATLAB. In order to get the desired output, the proportionality of hidden layers are semi-optimized to precise level but it may vary depending upon the training data set and the type of problem.

1. Introduction

This paper analyses the proportionality of neurons in multiple layers of Back Proportion Neural Network. Recognition is a machine learning technique i.e., data mining technique used to find out group membership for data instances. The purpose of neural networks is to make simpler the problems of prediction and recognition. Neural networks are easy models of biological neuron system. However, there are different learning mechanisms exist to enable the neural network acquire knowledge.

This biological neuron system is an equally distributed system made up of highly interconnected neurons thereby making it available for use and acquires knowledge. Based on the learning mechanisms and other features neural networks architectures have been classified into various categories. Training has been defined as the method of learning and the ability to solve a problem with the help of knowledge acquired is known as presumption.

The design and configuration of neural network is inspired by Human Brain, it is imitation of central nervous system, hence, performs functions similar to human brain. The functioning and structural constituent of human brain known as neurons performs computations such as cognition, pattern recognition, and logical inference. Therefore, relating to this the technology which has been built on the structure like human brain has been given the name Artificial Neural Network (ANN) or Artificial Neural System (ANS) or simply neural network. Additional names for this technology are termed as Connectionist networks, Neuro Computers, parallel distributed processors etc. Neural networks are known by other names also neurodes, Processing Elements and nodes. Properties of neural networks are as follows:

1. The NNs have the capability to map the input and output patterns i.e., they have mapping capabilities, they map the input patterns associated to the desired output patterns.
2. Examples are very important in training process of NNs. Thus, NN architectures could be trained with recognized examples of a problem before they are tested for their inference capability on unknown instances of the problem.
3. Neural networks possess the ability to generalize i.e., they may predict new outcomes from past trends.
4. NNs models real world problems i.e., they are robust and fault tolerant. They may recall full patterns from noisy patterns also.
5. NNs are multitasking also i.e. they may process information in parallel at a high speed and in undistributed manner.

The Neural network has the definition in the name itself; the term network describes the interconnection between neurons in the various layers of the system. Every NN system is basically a 3 layered structure Input layer, Hidden layer and Output layer. The input layer has got the input neurons which transfers the data to the hidden layer via synapses. In the same way the hidden layer transfers this data to the output layer via more synapses. The functioning of synapses is to store the value known as weights; it helps in manipulating the input and output to various layers. ANN can be defined on the basis of three characteristics:

- The Architecture: The number of layers and the number of nodes in each of the layers.
- The learning mechanism which is applied for updating the weights of the connections.
- The activation functions have been used in various layers.

2. Standard BPNN algorithm

BPNN has the capability of self-learning, which has two parts. The first one is forward transfer of information and the other one is the reverse transfer of error between expected output and the actual output. As shown in Fig. 1, the structure of BPNN has three layers: Input layer, hidden layer and output layer.

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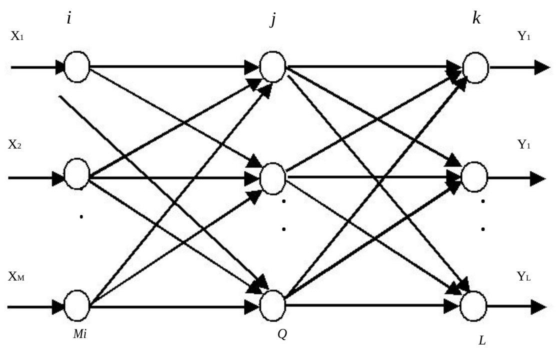

Fig. 1. BP neural network model.

The input layer of network has M neurons, the hidden layer has Q neurons and output layer has L neurons. The input vector of neural network is X = [x1, x2……..xM]. The output vector of neural network is Y = [y1, y2……yL].

The weighted value between input layer and hidden layer is wij and the weighted output between hidden layer and output layer is wjk. The transfer function of neural network is unipolar sigmoid function which is:

$$f(x) = \frac{1}{1+e^{x}}$$

The function has the characteristic which is:

$$f'^{(x)} = f(x)[1 - f(x)]$$

According to the gradient descent method, the data transmitted from input layer to hidden layer is l = xl. After the hidden layer receives data from input layer the first thing to be calculated is the weighted sum which is:

$$net_j = \sum_{i=1}^{M} w_{ij} x_i$$

and then transfer the data to the output layer through the transfer function. The output of hidden layer is:

$$O_j = f(net_j) = f\left(\sum_{i=1}^{M} w_{ij} x_i\right)$$

3. Literature review

Many scientists have researched about numeral character recognition till now and gave their reviews about the same. We have prepared the reviews about some of them.

Trenn (2008) considered the sufficiently smooth multivariable functions with a multilayer perceptron (MLP). For a given approximation order, explicit formulas for the necessary number of hidden units and its distributions to the hidden layers of the MLP are derived. The concept of approximation order encompasses Kolmogorov-Gabor polynomials or discrete Volterra series, which are widely used in static and dynamic models of nonlinear systems. His main contribution is that he has given the explicit formula for the necessary number of hidden units in an MLP to achieve a given approximation order. For linear and quadratic approximation, only one layer is needed. The correlation between approximation order and approximation accuracy was studied. A sufficient condition was given for the activation function for which a high approximation order implies high approximation accuracy.

Ke and Liu (2008) presented the neural network model, a new procedure and structure in nonlinear interpolation and demonstrates a potential of stock market prediction with incomplete, imprecise and noisy data. It presents a sensitivity analysis of optimal hidden layers and hidden neurons in neural network modeling for stock price prediction. To perform the sensitivity analysis forty cases with various hidden neurons are examined to estimate the training and the generalization errors. During the network training, the weights have to be updated in the forward and backward processes. In one forward and backward epoch, each weight must be perturbed twice and the error must be revaluated for each perturbation, so the error measurement in each hidden layer takes O(n) complexity for compute time, the total complexity required scales like O(nm) form hidden layers, where n is the number of weights in the network. It is very robust and simple to implement.

Caseiro and Ljolje (2013) presented techniques for building faster and more accurate recurrent neural network language modeling (RNNLMs). RNNLM have been shown to outperform most other advanced language modeling techniques.

An error rate reduction of 5.9% was observed on a state of the art multi-pass voice mail to test ASR system using RNNLMs trained with the proposed algorithm. He also showed that Brown clustering of the vocabulary is much more effective that other techniques.

They also presented an algorithm for converting an ensemble of RNNLMs into a single model that can be further tuned or adapted. They had shown that the word clustering algorithm used to decompose the output layer of a RNNLM is critical, and that using algorithms such as Brown clustering that take into account the context of words leads to substantial reductions in perplexity relative to simpler word frequency brining approaches. When evaluated on a state of the art ASR system, this technique proved to be superior to linear interpolation and achieved a 5.9% error rate reduction relative to the n-gram base line.

Muthukumar and Black (2014) introduced Speech Synthesis Systems. Synthesis systems are typically built with speech data and transcriptions. It is tried to build synthesis systems when no transcription or knowledge about the language are available. An automated way of obtaining phones and phonetic knowledge about the corpus is proposed by making use of Articulatory Features (AFs). An Articulator feature predictor is trained on a bootstrap corpus in an arbitrary other language using a three hidden layer neural network. This neural network runs on the speech corpus to extract AFs. Hierarchical clustering is used to cluster the AFs into categories i.e., phones. Phonetic information about each of these inferred phones is obtained by computing the mean of the AFs in each cluster. A Text-to-Speech synthesis system or synthesis in a speech to Speech translation system must work from text rather than raw phones. At this point, the ease with which the inferred phones can be predicted from text is unknown. This is an issue that is planned to investigate in the future work.

Sheela and Deepa (2011) backed propagation algorithm for neural networks. The objective is to analyze the parameters such as momentum and learning rate using back propagation algorithm in artificial neural networks. The results are obtained using two variation of back propagation algorithm: simple back propagation and back propagation with momentum. Simulation result shows affect the performance of ANN.

Sheela and Deepa (2013) proposed a new algorithm to find hidden neurons in Radial basis function networks for wind speed prediction in renewable energy systems. To find the number of hidden neurons, 101 various criteria examined based on the error values of mean squared error, mean absolute percentage error and mean absolute error. The minimal error values are considered as the best solution to find hidden neurons in RBFN. The proposed algorithm is tested on real time wind data.

Liu et al. (2007) proposed a novel and effective criterion based on the estimation of the signal to noise ratio figure (SNRF) to optimize the number of hidden neurons in neural networks to avoid over fitting in the function approximation. SNRF can quantitively measure the useful information left unlearned so that over fitting can be automatically detected from the training error only without use of a separate validation set. Without a priori knowledge of the noise characteristics of the training data may come with White Gaussian Noise (WGN) at an unknown level.

Tamura and Tateishi (1997) introduced Neural network theorems which state that only when there are infinitely many hidden units is a four-layered feed forward neural network equivalent to a three layered neural network. A proof is given showing that a three layered feed forward network with N – 1 hidden units can give any N input target relations exactly. Based on the results of the proof, a four-layered network is constructed and is found to give any N input –target relations with a negligibly small error using only (N/2)+3 hidden units. This clearly shows the difference in capabilities between a four layered feed forward neural network and a three layered feed forward neural network and indicates the superiority of the four layered network for the training of input target pairs.

Hunter et al. (2012) found out one of the major difficulties researchers facing using neural networks is the selection of the proper size and topology of the networks. A partial solution proposed to this problem is to use the least possible number of neurons along with a large number of training patterns. Neural network architectures vary in complexity and efficiency. The power of neural networks increases significantly with increased number of connections across layers. The most powerful are FCC architectures with the largest number of connections across layers per number of neurons.

However, with increased depth more nonlinear transformations are made and this may require higher accuracy of computing and larger sensitivity to noise.

Sahu and Raman (2013) proposed an efficient handwritten Devanagari character recognition system using neural network. Various techniques have been implemented for this problem with many improvements so far but mainly Artificial Neural Network technique is used to pre-process, segment and recognize Devanagari characters. The system was designed, implemented, trained and found to exhibit an accuracy of 75.6% on noisy characters. A small set of Devanagari characters using back propagation neural network is trained, then testing was performed on other word set. The accuracy of network was average. These characters are further analyzed and then tested with different set. Again the accuracy is analyzed. This process is repeated then again testing was performed on some new image sets written by different people. It was found that accuracy of the network increases in many cases. As the network is trained with more number of sets, the accuracy of recognition of characters increases.

Prasad and Kulkarni (2015) implemented Adaptive Neuro Fuzzy Classifier (ANFC) for recognition of isolated handwritten characters of Guajarati. They aimed to compare the performance of ANFC with weighted k – NN classifier proposed by them. Fuzzy classification is the task of partitioning a feature space into fuzzy classes. Authors used a supervised learning procedure based on Scaled Conjugate Gradient (SCG) algorithm to update parameters in an adaptive network. The recognition rates were recorded for 34 consonants of Guajarati. Maximum recognition efficiency of 88.89% was achieved for few characters using GPXNP feature.

Sazal et al. (2014) recognized Bangla handwritten character using Deep Belief Network with a focus on automatic learning of good representations. Among different learning structures, the deep learning structures, we employ the deep belief network (DBN) that takes the raw character images as input and learning proceeds in two steps: An unsupervised feature learning followed by a supervised fine tuning of the network parameters. In this approach, there is no need to create handcrafted features like loops, strokes and curves.

Dan and Xu (2013) introduced Back Propagation Neural Network based on offline handwritten digits recognition system The MNIST database of handwritten digits is applied to train and test the neural network. They introduced the principle component Analysis (PCA) for feature extraction which can improve the performance of the neural network and immensely shorten the training time. Comparisons being made depending on the recognition rate among three methods: Neural network method, thirteen features method, Fisher discriminant analysis method. After comparisons, Fisher discriminant analysis method has the lowest recognition rate and proved to be time consuming which is not suitable for smart phone application. BP neural network has itself too many nodes, which costs a lot of time in training. The thirteen features method need to calculate the minimum of the weighted distance from unclassified sample to all the training samples, so it occupies much more RAM. In order to increase the recognition rate we acquire the real-time learning method to adapt to the written style of the specific software user.

Neil and Liu (2014) introduced the Minitaur spiking network accelerator, an event driven neural network accelerator, which is designed for low power and high performance. As a field programmable gate array-based system, it can be integrated into existing robotics or it can offload computationally expensive neural network tasks from the CPU. In addition to the system's performance of 18.73 million PSCs /second, it consumes just 1.5 W of power, enabling it to be used in embedded robotics applications. With proper weights, the system is remarkably robust to noise.

Mitrpanont and Imprasert (2011) introduced Thai Handwritten Character Recognition using Heuristic Rules Hybrid Neural Network. In this the neural network technique is applied to identify and recognize the zigzag pattern. The proposed functions are mainly in Feature extraction enhancement to improve the feature conflict resolution rule and the specialized neural network based zigzag feature extraction and neural network based recognition. The result showed that the additional feature conflict resolution rule could achieve the feature extraction rate of 87.85%, specialized neural network based zigzag extraction could achieve 90.48%, neural network based recognition which combine both of the two proposed feature extraction functions could achieve 92.78%.

Ouchtati et al. (2014) proposed an offline system for the recognition of the handwritten numeric chains, their main objective is to determine the parameter vector who gives the best performances. They did their work and divided it into two parts:

The realization of system of isolated digits recognition, based mainly on the evolution of neural network performances, trained with the gradient back propagation algorithm and fed by several parameter vectors.

4. Problem formulation

The aim of this study is to figure out the merits of learning as well as recognition rate of handwritten numerals. The main reasons of less recognition rate of numerals is the extraction features from handwritten characters to train neural network so that its recognition accuracy is better and we have studied in the previous works that hidden layer plays a very important role in enhancing the learning rate of neural network and recognition accuracy. The whole neural network is divided into two phases:

1) Training or learning phase
2) Recognition phase

5. Proposed methodology

There are several steps in the proposed methodology as follows:

I. Declare all the variable to create simulation environment.

II. Pre-process the template image of handwritten numerals to train the neural network.
III. Create the neural network with proposed weights and neurons and initialize with proposed modes.
IV. Start training of neural network with 5 hidden layers.
V. The training will repeat for given number of epochs.
VI. Compare the network output with the target output and keep repeating the training process until the targeted output.
VII. After achievement of targeted output save the neural network for further recognition process.

The Recognition algorithm for five hidden layer BP-NN approach:

I. Load the trained neural network for 5 hidden layers.
II. Browse handwritten numerals image for recognition.
III. Select area of image to recognize.
IV. Pre-process image after selection.
V. Start comparison process using neural network.
VI. After recognition display the recognized numerals.

There are two phases of the work:

I. Training phase
II. Testing phase

5.1. Training phase

In the training phase, the neural network system has been provided with information patterns. The information patterns are in the form of 10*10 matrix. Each element can have only two values either a 0 or a 1.

5.2. Testing phase

In the testing phase, the patterns for the alphabets, numerals or symbols are entered into the system in either correct form with some errors in the element values. These patterns are compared with the ones in the knowledge base that was prepared by the training phase of the network. It recognizes the patterns by comparing the weights of every element in the pattern matrix with the elements in the knowledge base of the corresponding matrix. The number of iterations depends upon the choice of number of hidden layers.

6. Conclusion

In this paper we have reviewed that with the help of multiple hidden layer phenomena how a character recognition program is designed. After studying and reviewing many approaches to recognize the handwritten numerals it is concluded that BPNN gives best results in comparison to other methodologies. BP-NN performs better results and we have seen keeping the proportionality the performance increases with the increase in hidden layers. It can be declared from the study that if the number of hidden layers increases than three, the recognition rate for handwritten numeral network is higher for various languages e.g., Hindi, English, Tamil, Telegu, Arabic etc.

In this section five hidden layers have been given, which will significantly give high recognition rate and lesser learning time.

References

Caseiro D and Ljolje A (2013). Multiple parallel hidden layers and other improvements to recurrent neural network language modeling. In the 2013 IEEE International Conference on Acoustics, Speech and Signal Processing, IEEE, Vancouver, Canada: 8426-8429. https://doi.org/10.1109/ICASSP.2013.6639309

Dan Z and Xu C (2013). The recognition of handwritten digits based on BP neural network and the implementation on android. In the 2013 3rd International Conference on Intelligent System Design and Engineering Applications, IEEE, Hong Kong, China: 1498-1501. https://doi.org/10.1109/ISDEA.2012.359

Hunter D, Yu H, Pukish III MS, Kolbusz J, and Wilamowski BM (2012). Selection of proper neural network sizes and architectures—A comparative study. IEEE Transactions on Industrial Informatics, 8(2): 228-240. https://doi.org/10.1109/TII.2012.2187914

Ke J and Liu X (2008). Empirical analysis of optimal hidden neurons in neural network modeling for stock prediction. In the 2008 IEEE Pacific-Asia Workshop on Computational Intelligence and Industrial Application, IEEE, Wuhan, China, 2: 828-832. https://doi.org/10.1109/PACIIA.2008.363

Liu Y, Starzyk JA, and Zhu Z (2007). Optimizing number of hidden neurons in neural networks. In Proceedings of the IASTED International Conference on Artificial Intelligence and Applications (AIA '07): 121–126.

Mitrpanont JL and Imprasert Y (2011). Thai handwritten character recognition using heuristic rules hybrid with neural network. In the 2011 8th International Joint Conference on Computer Science and Software Engineering (JCSSE), IEEE, Nakhon Pathom, Thailand: 160-165. https://doi.org/10.1109/JCSSE.2011.5930113

Muthukumar PK and Black AW (2014). Automatic discovery of a phonetic inventory for unwritten languages for statistical speech synthesis. In the 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, Florence, Italy: 2594-2598. https://doi.org/10.1109/ICASSP.2014.6854069

Neil D and Liu SC (2014). Minitaur, an event-driven FPGA-based spiking network accelerator. IEEE Transactions on Very Large Scale Integration (VLSI) Systems, 22(12): 2621-2628. https://doi.org/10.1109/TVLSI.2013.2294916

Ouchtati S, Redjimi M, and Bedda M (2014). Realization of an offline system for the recognition of the handwritten numeric chains. In the 2014 9th Iberian Conference on Information Systems and Technologies (CISTI), IEEE, Barcelona, Spain: 1-6. https://doi.org/10.1109/CISTI.2014.6877040

Prasad JR and Kulkarni U (2015). Gujarati character recognition using adaptive neuro fuzzy classifier with fuzzy hedges. International Journal of Machine Learning and Cybernetics, 6(5): 763-775. https://doi.org/10.1007/s13042-014-0259-8

Sahu N and Raman NK (2013). An efficient handwritten Devnagari character recognition system using neural network. In the 2013 International Mutli-Conference on Automation, Computing, Communication, Control and Compressed Sensing (iMac4s), IEEE, Kottayam, India: 173-177. https://doi.org/10.1109/iMac4s.2013.6526403

Sazal MMR, Biswas SK, Amin MF, and Murase K (2014). Bangla handwritten character recognition using deep belief network. In the 2013 International Conference on Electrical Information and Communication Technology (EICT), IEEE, Khulna, Bangladesh: 1-5. https://doi.org/10.1109/EICT.2014.6777907

Sheela K and Deepa S (2011). Analysis of computing algorithm using momentum in neural networks. Journal of Computing, 3(6): 2151-9167.

Sheela KG and Deepa SN (2013). A new algorithm to find number of hidden neurons in radial basis function networks for wind speed prediction in renewable energy systems. Journal of Control Engineering and Applied Informatics, 15(3): 30-37.

Tamura SI and Tateishi M (1997). Capabilities of a four-layered feed forward neural network: Four layers versus three. IEEE Transactions on Neural Networks, 8(2): 251-255. https://doi.org/10.1109/72.557662

Trenn S (2008). Multilayer perceptrons: Approximation order and necessary number of hidden units. IEEE transactions on neural networks, 19(5): 836-844. https://doi.org/10.1109/TNN.2007.912306