Neural Network for Winner take All Competition using Palm Print Recognization

K. Karthikeyan L. Anusha E. Janani K. Mekala
Assistant Professor, Dept of CSE, SNS College of Engineering, CBE-107, TamilNadu, India.
UG Scholar, Dept of CSE, SNS College of Engineering, CBE-107, TamilNadu, India.

ABSTRACT:
Winner take all competition (WTA) widely takes place in many application to predict the winner of the participants. Many mathematical models are proposed to describe the phenomena discovered in different fields. It's is often difficult to explain the underlying mechanism of such a competition from the perspective of the feedback based on sophisticated models. Existing system do not have database also their accuracy and complexity is less. In this paper we present a simple form, which produces the WTA by taking advantages of selective positive negative feedback through interaction of neurons and also we have used the palm print images of the individuals in order to extract the features. For the feature extraction we use adaptive histogram equalization (AHE) and Gray layer co-occurrence matrix algorithm (GLCM).line feature points are used for the feature extraction by recognizing the vein.

Keywords:
Winner take all, competition, selective positive negative feedback, recurrent neural network, adaptive, Histogram equalization (AHE), Gray layer co-occurrence matrix algorithm (GLCM).

1. INTRODUCTION:

Winner take all (WTA) refers to the phenomena in which agent is a group compete with each other for activation and only the one with the highest input stays active and all other get deactivated. It widely exists in nature and society. For most plants, the main central stem, which only appears slightly shorter than the other side stems at the very beginning of the plant development, grows more and more strongly and eventually dominates over the others. It has been observed in society that, once a firm gets ahead, it is more likely to become better and better over time while the others will fall further behind. Neuroscientists find that the contrast gain in the visual systems comes from a WTA competition among overlapping neurons.

The Neural Network takes the participants positive negatives as input (u1,u2……un) and produces the predictable attribute value of the data mining model as output(x1,x2…..xn). A Neural Network involves input layer, hidden layer and output layer. Input layer define all the input attribute, hidden layer is the various probabilities of the input (assigned weights) and the output layer represents predictable attribute values of the data mining models. The weight in the hidden layer describes the relevant or important of particular inputs assigns.

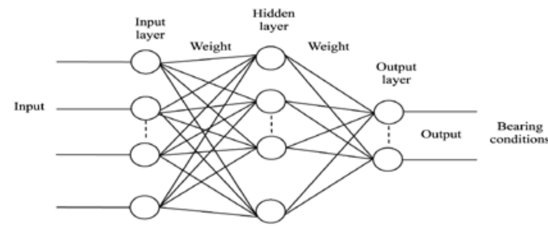

Fig 1.1: neural network architecture

An artificial neural network is an interconnected group of nodes, skin to vast network of neurons in a brain. Here, each circular nodes represent an artificial neuron and an arrow represent a connection from the output of the one neuron to the input of the another neuron. In an artificial neural network simple artificial nodes, called "neurons", "neurodes", "processing elements" or "units", are connected together to form a network which mimics a biological neural network. Neural network are also similar to biological neural network in performing function collectively and in parrlel by the units, rather than there being a clear delineation of subtask to which various units are assigned.

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics. The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. GLCM introduced by Haralicks contains information about the positions of pixels having similar gray level values.

For images which contain local regions of low contrast bright or dark regions, global histogram equalization won't work effectively. A modification of histogram equalization called the Adaptive Histogram Equalization

Manuscript received March 5, 2015
Manuscript revised March 20, 2015

can be used on such images for better results. Adaptive histogram equalization works by considering only small regions and based on their local cumulative distributive function (CDF), performs contrast enhancement of those region.

2. ITERATURESURVEY

[A] Shuai Li, Bo Liuanda Yangming Li, "Selective Positive- Negative Feedback Produces the Winner-Take-All Competition in Recurrent Neural Network" , Vol 24, No.2, FEBRUARY 2013

The winner take all (WTA) competition is widely observed in both inanimate and biological media and society. This model has an explicit explanation of the competition mechanism. The ultimate convergence behavior of the model proved analytical. Both theoretical and numerical results validate the effectiveness of the dynamic equation describing the nonlinear phenomena of WTA competition. The optimization based approach solves the problem accurately such as saturation function, matrix multiplication of the state vector, etc are often necessary in the iterations to approach the desired solution and thus are often computationally intensive. The resulting in dynamic is often complicated and are often difficult to explain the WTA mechanism. In this model a normalized recurrent neural network and the use of the general norm on modeling the power of signals. A recurrent neural network with a general p-norm is the regulation term for the WTA competition.

$$x_i = c_0\left(u_i - c_1\left||x|\right|^{p+1}{}_{p_{+1}}\right)|x_i|^p \mathrm{sgn}(x_i)$$

Where $x_i \in R$ denotes the state of the i neuron, $u_i \in R$ is the input and $u_i \geq 0, u_i \neq u_j$ for i≠j.

The ith neuron in the neural network receives input u_i and output x_i through the dynamic interaction with other neurons. The ith neuron is only connected to the central node, which computes the p-norm of the whole network state values. ||.|| represents the Euclidean norm.

In the simulation a time –variant signals as the input the input u is randomly generated between 0 and 1. The evolution of the state values of all neurons with time under different choice of the parameter p. It is single state and has a nonzero value eventually and the other state values are suppressed to the zero value.

The noise polluted neural network model considered in this part writes for the i th neuron as

$$x_i = c_0\left(u_i - c_1\left||x|\right|_{p_{+1}}{}^{p+1}\right)|x_i|^p \mathrm{sgn}(x_i) + v_i$$

[B] Huaguang Zhang, Bin Jiang, "LMI Based Approach for Global Asymptotic Stability Analysis of Recurrent Neural Networks with Various Delays and Structures" Vol 22, No 7, JULY 2011.

s In this system WTA is one layered structure it is established only in the statistical mean. Typical distributions of initial activations, the convergence behaviors of the existing and the proposed WTA neural network are evaluated theoretically. It suggested WTA neural network on average requirement fewer than $\log_2$ M iterations to complete WTA process, Where M is number of competitors. The pair-compared neural network (PACNET) is an eight-input multilayer feed-forward structure which is composed of pair comparison subnets which act to pick a maximum in a pair-by-pair hierarchy. The basic comparison subnet is for the two inputs. Each subnet picks the maximum of the two inputs and forwards to the next layer for further comparison. The output of the comparison subnet described as $z = 0.5f_r(x_1 - x_2) + 0.5f_r(x_1 - x_2) + 0.5x_1 + 0.5x\_2$,

Where the $f_r(.)$ is an ideal ramp functions

$$f_r(x) = \begin{cases} x \\ 0 \end{cases} \text{For } x \geq 0\,,\ x < 0$$

To the WTA process, uniformly distributed inputs are most difficult among three distributions to find the maximum activated neuron. The normally distributed inputs are used for the activation during random initialization. The peak uniform distribution is the input which is considerably larger. The maximum value is α, and the remaining (M-1) inputs are uniformly distributed in the range of [0, β]. The peak uniformly distributed inputs can be found in many classification problems in which the input exemplar matches well.

The WTA networks with lower convergence behaviors require a large number of iterations. The large number of iterations causes the error bounce to reduce. The error bound of the GEMNET is always greater than that of the MAXNET. The MAXNET requires more iteration to reach the convergence; its error bound will be further reduced. The GEMNET is much more robust to the offset error than the MAXNET.

The offset variation is the common phenomenon of the non ideal characteristics of the neural function. In general the second maximum activation has the most opportunity to erroneously become the winner when there are errors in the WTA networks. The original difference,Δ between the first two maximal activation assume that the offset errors of the neurons dealing with z_M and z_{M-1} are δ_1 and δ_2 respectively.

Compared to traditional iterative neural networks the GEMNET is not only equipped but it is a simplified one layer structure which is better than the multilayer PACNET but also with higher convergence speed than the MAXNET and PACNET.

3. PROBLEM IDENTIFICATION:

In many of the winner take all problem it's not possible to identify the eligible individual accurately due to the lack of pre-defined data's of the each and every individual. The existing system convergence speed is very low and also the output is not that much accurate. For individual reorganization and authentication, system such as histogram analysis is used where the recognisation and authentication is not that much accurate. For extracting the features from the image PCA technique is used which does not use the maximum values of the image and also do not extract the maximum values and feature from the image. The fuzzy neural network is used where compared to a common neural network, connection weights and propagation and activation functions of fuzzy neural networks differ a lot. The learning procedure is constrained to ensure the semantic properties of the underlying fuzzy system. A neuron-fuzzy system approximates a n-dimensional unknown function which is partly represented by training examples. .

4. PROPOSED SYSTEM:

Adaptive histogram equalization (AHE) is used for removing the noise from the image and also to authenticate the individual. By using the adaptive histogram equalization the image is preprocessed which can be used for the further process such as for extracting the features and to extract the result accurately. Following steps are carried out in adaptive histogram equalization:

1. Calculate a grid size based on the maximum dimension of the image. The minimum grid size is 32 pixels square.
2. If a window size is not specified chose the grid size as the default window size.
3. Identify grid points on the image, starting from top-left corner. Each grid point is separated by grid size pixels.
4. For each grid point calculate the CDF of the region around it, having area equal to window size and centered at the grid point.
5. After calculating the mappings for each grid point, repeat steps 6 to 8 for each pixel in the input image.
6. For each pixel find the four closest neighboring grid points that surround that pixel.
7. Using the intensity value of the pixel as an index, find its mapping at the four grid point based on their cumulative distribution function (CDFS).

In the proposed system gray layer co-occurrence matrix (GLCM) is used for feature extraction where the number of rows and columns is equal to the number of gray levels, G in the image. The matrix element P(i, j | d, θ) is the relative frequency with which two pixels, separated by distance d, and in direction specified by the particular angle (θ) , one with intensity i and the other with intensity j.

The GLCM algorithm is as follow:

1. Count all pairs of pixels in which the first pixel has a value i, and its matching pair displaced from the first pixel by d has a value of j.
2. This count is entered in the ith row and jth column of the matrix Pd [i, j]
3. Note that Pd[i,j] is not symmetric, since the number of pairs of pixels having gray levels[i,j]does not necessarily equal the number of pixel pairs having gray levels [j,i].
4. The elements of Pd [i, j]can be normalized by dividing each entry by the total number of pixel pairs.
5. Normalized GLCM N [i,j], defined by:

$$N[i,j] = \frac{p[i,j]}{\sum_i \sum_j p[i,j]}$$

By using this normalized value of the image other features such as energy, entropy, contrast and homogeneity are calculated.

Energy $= \sum_{i,j=0}^{N-i} \left(p_{ij}\right)^2$

Entropy $= \sum_{i,j=0}^{N-1} - \ln\left(p_{ij}\right) p_{ij}$

Contrast $= \sum_{i,j=0}^{N-1} p_{ij} (i-j)^2$

Homogeneity $= \sum_{i,j=0}^{N-1} \frac{p_{ij}}{1+(i-j)^2}$

'Contrast' is the intensity contrast between a pixel and its neighbor over the whole image. Range = [0 (size(GLCM,1)-1)^2].Contrast is 0 for a constant image.

'Correlation' is the statistical measure of how correlated as pixel is to its neighbor over the whole image. Range = [-1 1]. Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is NaN for a constant image.

'Energy' is the summation of squared elements in the GLCM. Range = [0 1]. Energy is 1 for a constant image.

'Homogeneity' is the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Range = [0 1]. Homogeneity is 1 for a diagonal GLCM.

These values are extracted from the normalized image which is done by using the Adaptive histogram equalization. After which the GLCM algorithm is used to identify the individual features such as energy, entropy, contrast, correlation and homogeneity. The values obtained using this GLCM technique is used by the neural network for the further process. The output of the neural network process gives the final result of the candidate who has registered for the participation that is either the person is selected or rejected. All this process is explained in the following flow chart which explains the entire process of the proposed system.

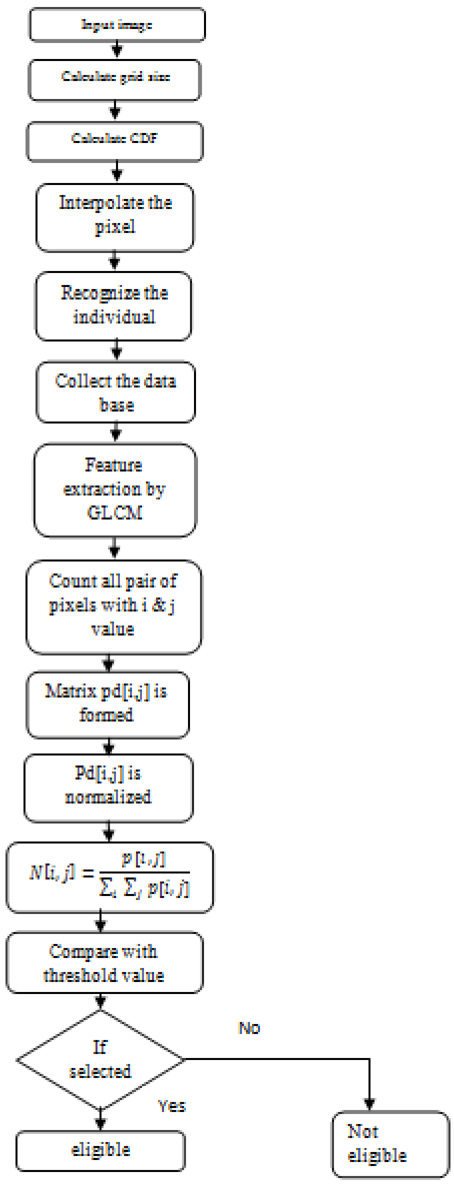

Fig 4.1: This flow chart describes the entire process involved in AHE technique, GLCM algorithm and neural network

A probabilistic neural network (PNN) is a feed forward neural network, which was derived from the Bayesian network and a statistical algorithm. In a PNN, the operations are organized into a multilayered feed forward network with four layers. PNNs are much faster than multilayer preceptor networks. PNNs can be more accurate than multilayer preceptor networks, relatively insensitive to outliers, generate accurate predicted target probability scores and approach Bayes optimal classification. PNN are slower than multilayer preceptor networks at classifying new cases and require more memory space to store the model.

4. RESULT AND DISCUSSION:

Table4.1: the following table represent the difference between the existing and proposed system.

SNO	TECHNIQUES	EXISTING	PROPOSED
1	Image reorganization	Histogram equalization (HE)	Adaptive Histogram Equalization (AHE)
2	Feature extraction	Principal Component Analysis (PCA)	Gray Layer Co-occurrence Matrix (GLCM)
3	Neural network	Fuzzy Logic Neural Network	Probabilistic Neural Network (PNN)

Fig4.2: output

CONCLUSION:

In this paper, a probabilistic neural network (PNN) is proposed to explain and generate the WTA competition and palm prints are used to authenticate the individual. In contrast to the existing system data set is used for extracting and storing the certain values of the competitors. The accuracy of the proposed system is increased by using the adaptive histogram equalization technique and also by the PNN. This system can be performed with both the static and dynamic inputs. The result validates the effectiveness of the proposed model.

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K.Karthikeyan is an Assistant Professor in the Department of Computer Science and Engineering at SNS College of Engineering, Coimbatore. He completed his B.E Computer Science and Engineering and M.E. in Industrial Engineering from various colleges at Anna University affiliated institution, Chennai. His areas of specializations are software Engineering, Soft Computing and Data Mining applications. He has published many papers in International and national conferences and journal. He is supervising 8 Engineering students at past and present. He is actively involved in department activities.

Anusha.L is currently pursuing BE Computer Science and Engineering in SNS college of Engineering. She is interested in Soft Computing.

Janani.E is currently pursuing BE Computer Science and Engineering in SNS college of Engineering. She is interested in Soft Computing.

Mekala.K is currently pursuing BE Computer Science and Engineering in SNS college of Engineering. She is interested in Soft Computing.