A Simple Feature Extraction Technique of a Pattern By Hopfield Network

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Abstract-

Interest in the area of pattern recognition has been increasing rapidly due to emerging applications, which are not only challenging but also demanding. Feature extraction is a special form of dimensionality reduction in pattern recognition. Our goal is to introduce a simple feature extraction technique for pattern recognition. Pattern recognition is the study of how machines can observe the environment, learn to distinguish patterns of interest from their background and take reasonable decision about the categories of the patterns. During last 50 years of research, attempts have been made by different researchers to develop a general-purpose machine pattern recognizer depending on different algorithms like template matching, statistical approach, artificial neural network etc. In this paper an approach of scale and translation independent feature extraction technique has been presented and analyzed with the help of Hopfield network. This technique is very useful for extraction of feature of shape of an object. It can be applied in the area of image processing, synthetic aperture radar, robotics etc., where detection of shapes of a digitized image or video stream are required.

Keywords: Pattern Recognition, Feature Extraction, Hopfield Network

1. Introduction

Neural networks can be viewed as massively parallel computing systems consisting of an extremely large number of simple processors with many interconnections. Neural network models attempt to use some organizational principles (such as learning, generalization, adaptivity, fault tolerance, distributed representation, computation etc.) in a network of weighted and directed graphs in which the nodes are artificial neurons and directed edges are connections between neuron outputs and neuron inputs. The main characteristics of neural networks are that they have the ability to learn complex nonlinear input-output relationships. The most commonly used family of neural networks for pattern classification tasks are the feed-forward Artificial Neural Networks (ANNs) [3], recurrent networks [8], the ART networks [6], Hopfield ANNs [1,7] etc. Here a neural network is used to extract the feature of the pattern based on pixel data. Initially a known pattern is transformed to intensity image and histogram equalization is done for contrast improvement. Then it is resized by nearest neighbor interpolation in a square matrix of size 256×256. The matrix is then normalized and considered as an adjacency matrix of an asymmetric Hopfield network with self-loops. The input/output characteristic of each unit of Hopfield network is considered as sigmoidal form. The values of the output of all units of Hopfield network after attaining equilibrium are collected in a one-dimensional array of 256 elements and this is the feature of the pattern.

Here 500 simple patterns are tested and results obtained are really promising and encouraging. Here few examples of simple patterns are given.

2. Formulation

For learning, the single known pattern is transformed to a gray scale image of class double with 256 levels where 0 represent black and 255 represent white. Then histogram of the pattern is equalized. The mapping function of histogram equalization is given by.

$$N(g) = Max\left\{0, Round\left(\frac{2^l.c(g)}{m.n}\right) - 1\right\} \ldots\ldots\ldots\ldots \text{(1)}$$

Where *N(g)* is the new gray value, *c(g)* is the cumulative pixel count up to old gray level *g*, *Round* implies a rounding to the nearest integer value, *m* and *n* are the number of rows and columns of original image respectively and here *l* is 8 for 256 levels.

After histogram equalization the image is resized by nearest neighbor interpolation in a square matrix of size 256×256. After normalization with respect to the maximum element value, the matrix is considered as adjacency matrix of a Hopfield network and the input/output characteristic of each unit is taken as sigmoidal form. So the output of *j*th unit is given by:

$$y_j = \frac{1}{1 + \exp\left[-\lambda\left(\sum_{i=1}^{n} w_{ij} y_i - \theta_j\right)\right]} \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

where *n* is the number of units, λ (0.02 here) is the activation gain and θ_j (zero here) is the threshold.

For a 256×256 matrix there are 256 units or vertices in the network. Initially 256 number of random numerical values, which are always less than unity and greater than zero, are assigned to each of the 256 units of the network [4]. Thereafter the value of each unit is calculated asynchronously when the value of all other units are kept unchanged at the initially assigned values. For a unit the difference between assigned value and calculated value is the error of that unit. Now a variable fraction (increasing with the number of iterations) of error is subtracted from the initially assigned value. After subtraction the new value is assigned to each unit. Continuing this procedure repeatedly when the magnitude of average error becomes less than 10^{-5}, the system is assumed to be in equilibrium and the last assigned value to each unit is termed as the value of that unit under equilibrium. So a feature vector is formed with 256 elements.

In recognition, following the same procedure a vector of 256 elements is formed by Hopfield network. It is observed that, if the separable patterns are placed along the main diagonal of the matrix without overlapping, the array can be partitioned for different patterns. After normalization of the vector obtained by Hopfield network the point where the numerical value of the array is changed from one to less than one, this point is considered as a starting point of a pattern and where the value is again changed from less than one to one, the point is considered as the end point of the pattern. Observing these changes in the array, number of patterns is detected. And the array is partitioned accordingly. For a single pattern or overlapping patterns there is only one change for each case (i.e. one to less than one and less than one to one). So the boundary of only one pattern is detected. In each case (more than one pattern or single pattern) after detecting the boundary of patterns, the one-dimensional array is resized to 1×256 matrix by nearest neighbor interpolation.

3. Results

The system is trained for 1000 simple patterns. And the system is tested for 500 patterns. The features of four simple patterns (figure 1) are shown here (figures 2a to 2d). It is tested with a pattern where four patterns are placed diagonally (figure 3). The output of Hopfield network is plotted after normalization in figure 4. After partitioning the output of Hopfield network the pattern is recognized in each case. Reconstruction of the patterns in the patterns of figure 3 from table is shown in figure 5.

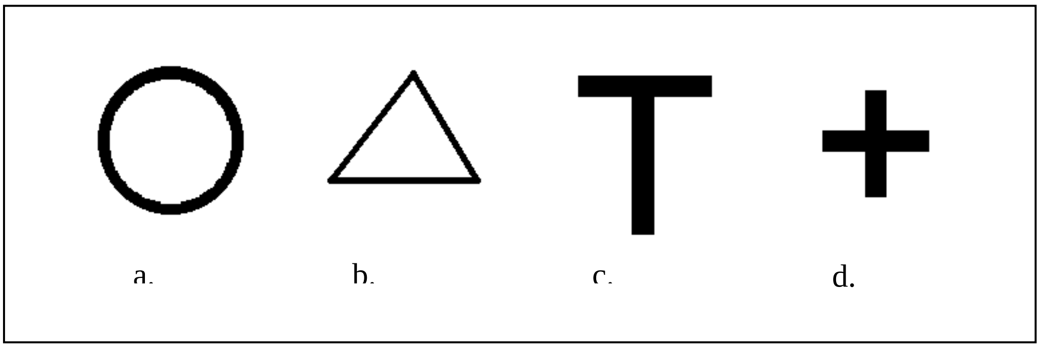


Figure 1: Different Simple Pattern For Training

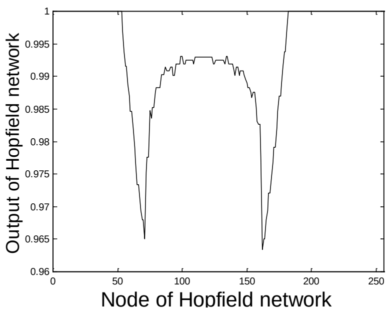


Figure 2(a): Output of Hopfield Network for Pattern of Figure1a.

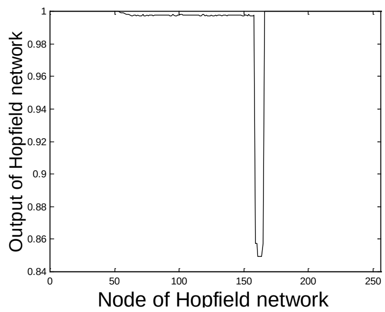
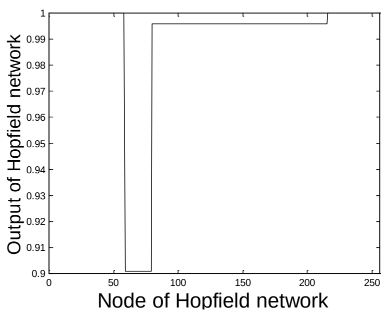


Figure 2b: Output of Hopfield Network for Pattern of Figure 1b.



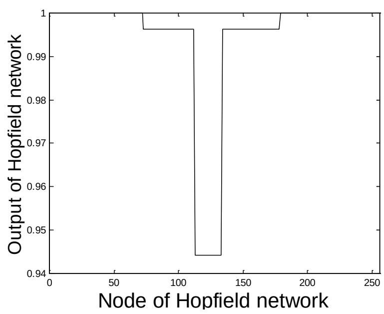


Figure 2c: Output of Hopfield Network for Pattern of Figure 1c.

Figure 2d: Output of Hopfield Network for Pattern of Figure 1d.

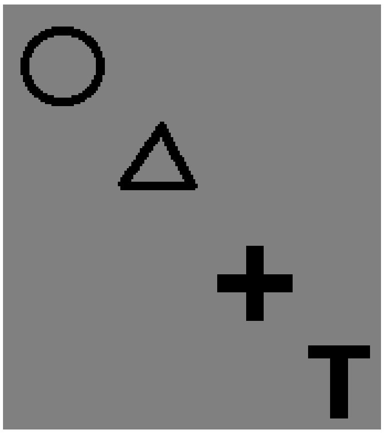


Figure 3: Pattern for Recognition

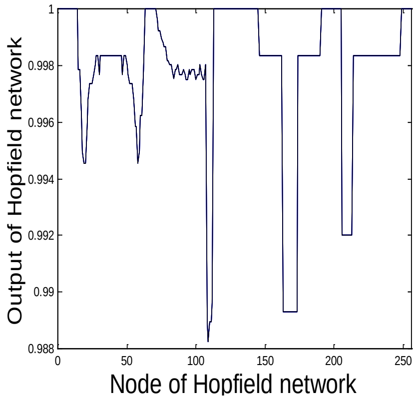


Figure 4: Output of Hopfield Network for Pattern of Figure 3

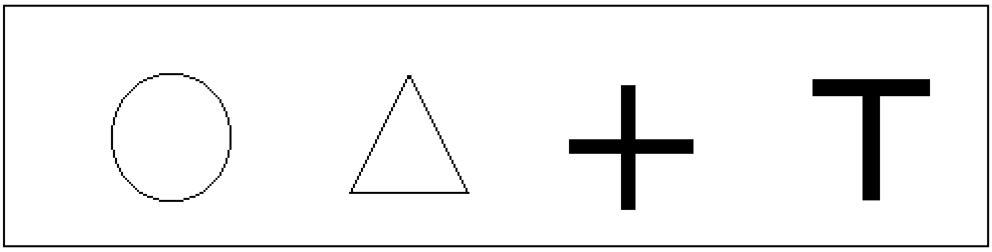


Figure 5: Reconstruction of the Elements in the Pattern of Figure

4. Conclusions

A neural network base feature extraction technique is presented in this paper. The technique, described here is very simple and efficient one. The system is successfully tested for 500 different patterns. If different patterns are placed in such a way that the pattern matrix is not a diagonal one, the output from the Hopfield network can't be partitioned for different patterns. In that case two dimensional wavelet analysis may be used to separate the patterns or the combinations of different patterns may be treated as a single pattern and the networks may be trained for that single pattern.

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