Review Analysis of Pattern Recognition by Neural Network

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***Abstract—Pattern* recognition basically assigns a label to a given input image. Pattern recognition is done on the basis of classes to which an input image belongs. A pattern could be a fingerprint image, a handwritten cursive word, a human face, or a speech signal.**

In this paper we consider to analyze back propagation algorithm and feed forward algorithm used for recognizing patterns. We also try to implement Leaky integrate and fire neuron model which belongs to a category of Spiking neural networks.

Keywords- Back propogation Algorithm, Feed Forward Algorithm, LIF-model, Spiking Neural Network.

I. Introduction

Pattern recognition basically assigns a label to a given input image. Pattern recognition is done on the basis of classes to which an input image belongs.

A pattern could be a fingerprint image, a handwritten cursive word, a human face, or a speech signal. Given a pattern, its recognition/classification may consist of one of the following two tasks:

1) supervised classification (e.g., discriminant analysis) in which the input pattern is identified as a member of a predefined class,

2) unsupervised classification (e.g., clustering) in which the pattern is assigned to a hitherto unknown class.

Thus, pattern recognition is a popular application that enables the full set of human perception to be acquired by machine. Neural network possesses the capability of pattern recognition. Researchers have reported various neural network models capable of pattern recognition, models that have the function of self organization and can learn to recognize patterns. It is implemented in following steps:

In the training stage (Approximation), neural networks extract the features of the input data [1].

In the recognizing stage (generalization), the network distinguishes the pattern of the input data by the features, and the result of information is greatly influenced by the hidden layers. Neural-network learning can be specified as a function approximation problem where the goal is to learn an unknown function (or a good approximation of it) from a set of input-output pairs. Every instance in any dataset used by machine learning algorithms is represented using the same set of features. The features may be continuous, real coded, categorical or binary. If instances are given with known labels (the corresponding correct outputs) then the learning is called supervised, in contrast to unsupervised learning, where instances are unlabeled. In our paper we consider the data set of alphabets.

Various algorithms are being used for this based on neural networks. Neural Networks are effective tool used in this reference.

In this paper we consider to analyze back propagation algorithm and feed forward algorithm used for recognizing patterns. We also try to implement Leaky integrate and fire neuron model which belongs to a category of spiking neural networks [1].

II. Neural Background

A. *Artificial Neural Network*

Neural network is an inter connection of various small processing units called neurons or Neuroides. An artificial neural network is an adaptive mathematical model or a computational structure that is designed to simulate a system of biological neurons to transfer information. The main characteristics of neural networks are that they have the ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data [2].

An Artificial Neural Network (ANN), usually called neural network (NN), is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation (Figure 1). In most cases, ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase [2].

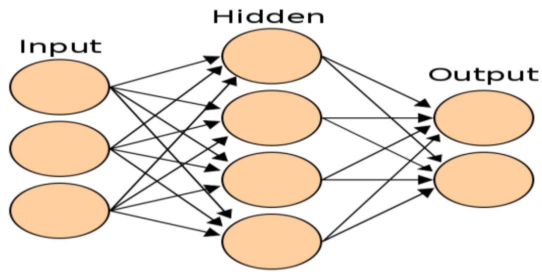


Figure 1. Artificial Neural Network structure.

B. *Spiking Neural Networks*

Spiking Neural networks (SNNs) fall into the third generation of neural network models, increasing the level of realism in a neural simulation. In addition to neuronal and synaptic state, SNNs also incorporate the concept of time into their operating model. The idea is that neurons in the SNN do not fire at each propagation cycle (as it happens with typical multi-layer perceptron networks), but rather fire only when a membrane potential – an intrinsic quality of the neuron related to its membrane electrical charge – reaches a specific value. When a neuron fires, it generates a signal which travels to other neurons which, in turn, increase or decrease their potentials in accordance with this signal [3].

A spiking neural network model is used to identify characters in a character set. The network is a two layered structure consisting of integrate-and-fire and active dendrite neurons. There are both excitatory and inhibitory connections in the network. Spike time dependent plasticity (STDP) is used for training. It is found that most of the characters are recognized in a character set consisting of 48 characters.

Following figure shows the result of character recognition performed individually along with the data set used [4].

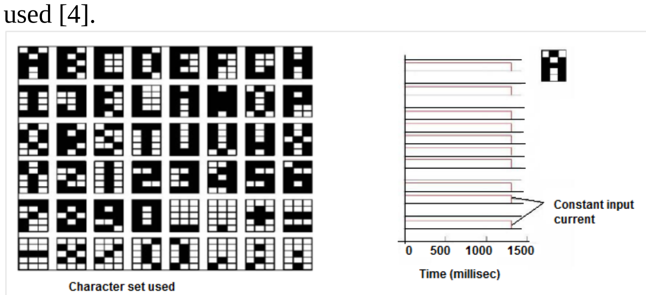


Figure 2. Output when each character is presented individually.

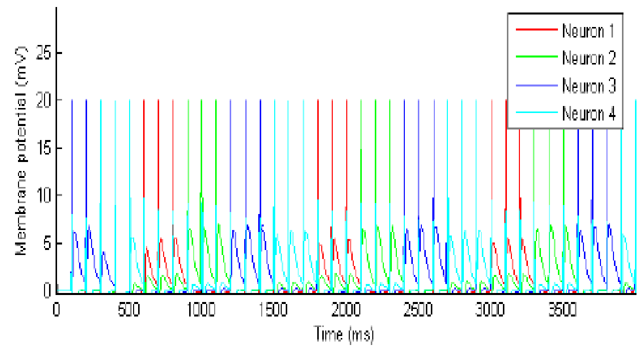


Figure 3. Output when characters are presented in following order: 'C', 'D 'A', 'B', 'C', 'D' [3].

C. *Integrate and fire model*

The leaky integrate-and-fire neuron introduced is probably the best-known example of a formal spiking neuron model [3]. All integrate-and-fire neurons can either be stimulated by external current or by synaptic input from presynaptic neurons.

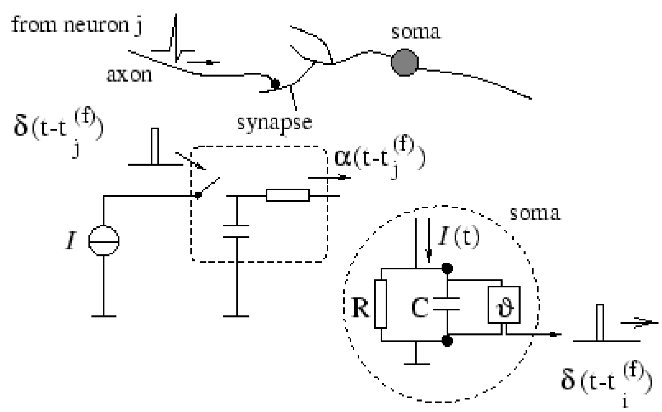


Figure 4. Schematic diagram of the integrate-and-fire model [3].

The basic circuit is the module inside the dashed circle on the right-hand side. A current I(t) charges the RC circuit. The voltage u(t) across the capacitance (points) is compared to a threshold ϑ. If $u(t) = \vartheta$ at time $t_i(f)$ an output pulse $\delta(t - t_i(f))$ is generated. On the left part: A presynaptic spike $\delta(t - t_j(f))$ is low-pass filtered at the synapse and generates an input current pulse $\alpha(t - t_i(f))$.

The basic circuit of an integrate-and-fire model consists of a capacitor C in parallel with a resistor R driven by a current I(t). The driving current can be split into two components, I(t) = IR + IC. The first component is the resistive current IR which passes through the linear resistor R. It can be calculated from Ohm's law as IR = u/R where u is the voltage across the resistor. The second component IC charges the capacitor C. From the definition of the capacity as C = q/u (where q is the charge and u the voltage), we find

a capacitive current IC = C du/dt.

$$I(t) = \left(\frac{u(t)}{R}\right) + C\left(\frac{du}{dt}\right) \tag{1}$$

We multiply the above equation by R and introduce the time constant of the `leaky integrator'. This yields the standard form :

$$\tau m \frac{du}{dt} = -u(t) + Ri(t) \tag{2}$$

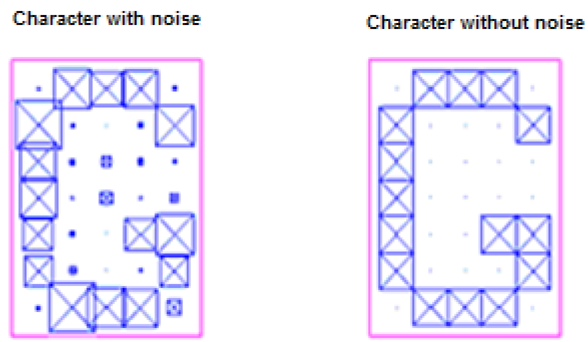
We refer to as the membrane potential and to as the membrane time constant of the neuron.

III. System Overview

A. Backpropagation Algorithm for Pattern Recognition [4]

Backpropagation learning emerged as the most significant result in the field of artificial neural networks. The backpropagation learning involves propagation of the error backwards from the output layer to the hidden layers in order to determine the update for the weights leading to the units in a hidden layer. The error at the output layer itself is computed using the difference between the desired output and the actual output at each of the output units. The actual output for a given input training pattern is determined by computing the outputs of units for each hidden layer in the forward pass of the input data. The error in the output is propagated backwards only to determine the weight updates.

The reliability of the neural network pattern recognition system is measured by setting the network with hundreds of input vectors with varying quantities of noise. The script file tests the network at various noise levels, and then graphs the percentage of network errors versus noise. Noise with a mean of 0 and a standard deviation from 0 to 0.5 is added to input vectors. At each noise level, 100 presentations of different noisy versions of each letter are made and the network's output is calculated. The output is then passed through the competitive transfer function so that only one of the 26 outputs (representing the letters of the alphabet), has a value of 1. The number of erroneous classifications is then added and percentages are obtained. The example with alphabet 'G' is shown in Figure 4 [4].



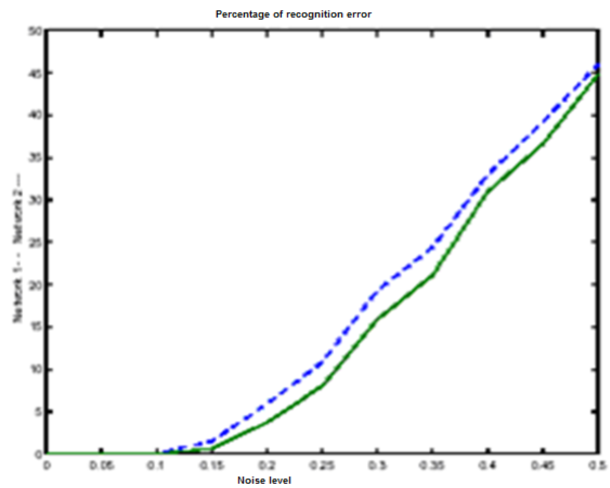


Figure 5. Reliability for the Network Trained with and without Noise [3].

The solid line on the graph shows the reliability for the network trained with and without noise. The reliability of the same network when it had only been trained without noise is shown with a dashed line. Thus, training the network on noisy input vectors greatly reduces its errors when it has to classify noisy vectors. Then network did not make any errors for vectors with noise of mean 0.00 or 0.05. When noise of mean 0.2 was added to the vectors both networks began making errors. If a higher accuracy is needed, the network can be trained for a longer time or retrained with more neurons in its hidden layer. Also, the resolution of the input vectors can be increased to a 10-by-14 grid [4].

Other typical problems of the back-propagation algorithm are the speed of convergence and the possibility of ending up in a local minimum of the error function. Today there are practical solutions that make back-propagation in multi-layer perceptrons the solution of choice for many machine learning tasks.

B. Feed forward Neural Networks for Pattern Recognition

A feed-forward network can be viewed as a graphical representation of parametric function which takes a set of input values and maps them to a corresponding set of output values [2]. Figure 6 shows an example of a feed-forward network of a kind that is widely used in practical applications [2].

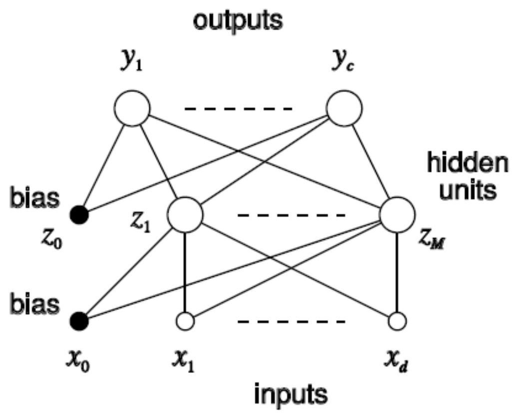


Figure 6. Feed-forward network.

Nodes in the above figure represent either inputs, outputs or `hidden' variables, while the edges of the graph correspond to the adaptive parameters. We can write down the analytic function corresponding to this network follows. The output of the hidden node is obtained by first forming a weighted linear combination of the d input values to give:

$$a_j = \sum_{i=1}^{d} u_{ji} x_i + b_j \qquad (3)$$

The value of hidden variable j is then obtained by transforming the linear sum in (3) using an activation function to give :

) (4)

Finally, the outputs of the network are obtained by forming linear combinations of the hidden variables to give :

$$a_k = \sum_{j=1}^{M} u_{kj} z_i + c_k \qquad (5)$$

The parameters are called weights while are called biases, and together they constitute the adaptive parameters in the network.

There is a one-to-one correspondence between the variables and parameters in the analytic function and the nodes and edges respectively in the graph.

In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network [2].

IV. Implementing LIF Neuron Model for Pattern Recognition [6]

Leaky Integrate and Fire (LIF) neuron can be applied to solve nonlinear pattern recognition problems. A LIF neuron is stimulated during T ms with an input signal and fires when its membrane potential reaches a specific value generating an action potential (spike) or a train of spikes.

Given a set of input patterns belonging to K classes, each input pattern is transformed into an input signal, then the spiking neuron is stimulated during Tms and finally the firing rate is computed. After adjusting the synaptic weights of the neuron model, we expect that input patterns belonging to the same class generate almost the same firing rate; on the other hand, we also expect that input patterns belonging to different classes generate firing rates different enough to discriminate among the different classes.

When the input current signal changes, the response of the LIF neuron also changes, generating different firing rates,

The firing rate is computed as the number of spikes generated in an interval of duration T. The neuron is stimulated during T ms with an input signal and fires when its membrane potential reaches a specific value generating an action potential (spike) or a train of spikes. Firing rate (fr) is given by fr = Fn/T

Where Fn= No of spikes generated and T= Input spike time period The accuracy (classification rate), achieved with the proposed method, was computed as the number of input patterns correctly classified divided by the total number of tested input patterns [6].

V. Conclusion and Futur Scope

Various algorithms are used for Pattern recognition. We can summarize that Back propagation algorithm method used is based on backward propagation of errors. It is mainly affected by noise.

A feed-forward network can be viewed as a graphical representation of parametric function which takes a set of input values and maps them to a corresponding set of output values .

Spiking neurons can be considered as an alternative way to perform different pattern recognition tasks. If only one neuron is capable to solve pattern recognition problems, perhaps several spiking neurons working together can improve the experimental results obtained. The input patterns belonging to the same class generate almost the same firing rate; on the other hand, input patterns belonging to different classes generate firing rates different enough to discriminate among the different classes.

However, implementing an LIF model for pattern recognition needs to be reanalyzed if patterns of different classes are applied at the input, at the same time, simultaneously.

In other we can say that, if input patterns of different classes are applied at the same time to an LIF model, then it may not produce correct firing rates and hence patterns may not be detected correctly.

This can be considered as one of the limitation or drawback of an LIF model which can be eliminated in future scenario.

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