A Survey: Artificial Neural Networks in Surveillance System

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ABSTRACT

Object recognition has been the subject of research interest in the last decade. Object recognition in traffic signals has been done with incorporation of most image processing techniques to enhance image. This processing of image involves the utilization of neural networks. So the sole purpose of this paper is to identify which neural network could bring in the great storage efficiency, quality, robustness, pattern completion, content addressable memory of the image (objects) recognition in the traffic signal systems. So, the extensive comparison has been done on these neural networks for the application. Most of the pattern mapping neural networks suffer from the drawbacks that during learning of weights, the weigh matrix tends to encode the presently active pattern, thus weakening the trace of patterns it had already learnt. The other problem that the common types of neural networks face is the forceful categorization of a new pattern to one of the already learnt classes. On occasions such categorization seems to be ridiculous as the nearest class of current pattern may be significantly different with respect to the center of the class. The problems of the lack of stability of the weight matrix and forceful categorization of a new pattern to one of the existing classes, has led to the proposal of a new architecture for pattern classification.

keywords

Video surveillance, Adaptive resonance network, artificial neural networks, plasticity-stability dilemma, Object recognition

1. PERCEPTRON MODEL

The perceptron is a simple model of a neuron. A perceptron has a number of external input pattern, one internal input, a threshold, and one output. All of the inputs have weights attached to the input patterns that modify the input values to the neural network. The perceptron is an algorithm for supervised classification of an input into one of two possible outputs.

Perceptron’s are continuous classifiers. The main feature of perceptron’s is that they can be trained to behave a certain way as all neural networks. The perceptron uses an activation function, the range of which is -1 to +1. The perceptron also has adjustable weights which can be used to train the perceptron to learn input patterns and generate the appropriate outputs.

The perceptron is an elegantly simple way to model a human neuron’s behavior. It is a single layer feed forward network. A feed forward architecture typically consists on an input layer of sensorial nodes, one or more hidden layers of neurons, and an output layer of neurons. Communication proceeds layer by layer from the input layer via the hidden layers up to the output layer.

The main complexity of perceptron learning algorithm can only represent linearly separable hypotheses but many real world domains are not linearly separable. The other problem faced by perceptron learning algorithm is that they select the search direction based on the incorrect classification of the previous output and not based on the information available. This might lead many options for choosing weights for adjustments.

2. ADALINE MODEL

ADALINE (Adaptive Linear Neuron or Adaptive Linear Element). Adaline is a single layer neural network with multiple nodes where each node accepts multiple inputs and generates one output. The difference between Adaline and the standard perceptron is that in the learning phase the weights are adjusted according to the weighted sum of the inputs (the net). In the cases of standard perceptron, the net is passed to the activation function and the function's output is used for adjusting the weights.

In the case of adaline model an error function is defined and according the error function the weights are chosen so as to minimize the error, where its weights are determined by the normalized least mean square (LMS) training law.

The basic structure of adaline is similar to a neuron with a linear activation and a feedback loop. During the training phase of ADALINE, the input vector as well as the desired output are present in the network.

Table 1. Perceptron and Adaline model

Model	Perceptron	Adaline
Type	Feed forward	Feed forward
Neuron layers	1 input layer 1 output layer	Many input layers 1 output layer
Input value types	Binary	Binary
Learning method	Hard limiter	Supervised
Learning algorithm	Hebb learning rule	Gradient descent
Application	Simple logical operations Pattern classification	Simple logical operations Regression

3. Hopfield Network

It is an unsupervised neural network. A recurrent artificial neural network founded by John Hopfield. Hopfield networks are the simplest artificial neural networks that incorporates three basic components integration, activation and learning .Hopfield network is generally of two types single layered and multilayered.

3.1 Incorporation of Hopfield in object detection

The coarse and fine strategy is implemented by utilizing multilayered Hopfield neural network because in single layered Hopfield there exists a multiple local minima which make it very difficult to predict the pattern.

3.2 Network

The network has the architecture of the cascading of several single layer Hopfield networks with interconnections between adjacent layers.

3.3 Modeling

The modeling involves several image pyramids for each input neurons. The inputs we take are the corners of the cars, buses (object) which tend to have high curvature point. For this polygon approximation algorithm is used to obtain the corners of the object at each level from the boundaries. This can be called as the model graph pyramid.

3.4 Construction

Construction is done with Energy function into consideration A= [A1 A2] where the entire state vector is the concatenation of the state vectors of the two layers (L1 and L2).A1 and A2 are the corresponding state vectors. So, by considering the connection weights, interconnection weights and rate of change of energy, an algorithm is devised to construct the Hopfield networks. The algorithm involves two termination strategies

1. Termination of local minima when output neurons are converged.

2. Termination of the algorithm when the output neurons are unchanged after a constant number of iterations.

3.5 Drawbacks

Although multi layered Hopfield neural networks helps us to escape the illusion of multiple local maxima, it is very difficult to analyze the Dynamics of energy function. This is also an approximation that local maxima thus obtained will more or less be equal to the global maxima.

4. Bidirectional Associative Memory

It is also an unsupervised neural network of recurrent type introduced by Bart Kosko. One major notable thing is the hetero-associativity, it can give an another pattern which of potentially of different size from the input pattern (neuron which in turn is the edges of the object).However, Hopfield network returns only the patterns which are of same size.

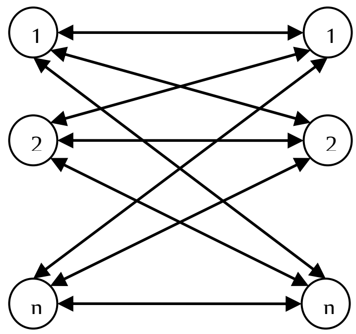

Fig 1: Bidirectional associative memory

4.1 Incorporation of Bidirectional Associative Memory in object detection

The input neurons we consider should be bipolar binary. So it consists of neurons arranged in two layers (L1 and L2). So the basic understanding is weight from the layer L1 to layer L2 is same as layer L2 to layer L1.

4.2 Modeling

We use clustering method to model the network, since this is an unsupervised network. There is no feedback mechanism or input's membership in a particular class. But the training set contains both input neurons and required responses. The characteristics of the neurons and initial weights are based on the training method of the network. The objects to be recognized are taken as patterns and hence the pattern grid thus formed is either 01 or 11. The following four parameters are considered for the relative comparison among other networks and this network.

1. Noise in weights

2. Noise in inputs

3. Loss of connections

4. Missing information

4.3 Construction

The basic architecture with an initializing vector b which is applied at the input to the layer A of neurons.

1. Association between pattern pairs that are stored in memory
2. Weights are calculated.
3. Test vector pair a, b is given as input.

4. Forward and backward pass of input.

4.4 Drawbacks

The logical symmetry of interconnection severely reduces the efficiency of BAM in object(pattern) storage and recall. The number of pattern pairs to be used is also limited. Also the random numbers are to be added to make the approximation.

5. Adaptive resonance theory

ART stands for "Adaptive Resonance Theory", invented by Stephen Grossberg in 1976. ART represents a family of neural networks. The basic ART System is an unsupervised learning model. The term resonance refers to a state in which category prototype vector finds a match which can be compared to the current input vector. ART matching leads to this state which leads the network to the process of learning. Thus, the network learns only in its resonant state. ART networks are self-organizing; they learn to categorize and recognize input patterns in the absence of teaching or supervisory signals. The most popular implementations of ART networks are known as ART 1 and ART 2. The ART 1 networks can handle binary input patterns, whereas the ART 2 class of networks was designed to handle continuous-valued or analog input patters.

Real world scenarios pose a challenge in which the data needs to change dynamically. Thus, every learning system in real world faces the plasticity-stability dilemma. The system must be in a state to learn to adapt to the dynamic changes in the environment. This property is called plasticity. But, this constant change can make the system unstable, because it keeps gaining new knowledge at the cost of already existing knowledge. This condition where a contradiction between plasticity and stability exists is called plasticity-stability dilemma. The back-propagation algorithm suffers from this dilemma. ART has been designed to solve this problem. It allows autonomous recognition and learning without any supervisory control or algorithmic implementation.

5.1 Stability-Plasticity Dilemma

This dilemma is faced by all learning systems. There are a few questions arising out of this dilemma. How can a learning system learn new things without forgetting its previous knowledge? How can the network remain plastic in response to a relevant and also remain stable to an irrelevant input? How can the neural network remain plastic enough to learn new patterns and also maintain its stability of the already learned patterns? Does the system possess the knowledge to switch between the plastic and stable modes? Does a method exist where the system can retain the previous knowledge while learning new things? Adaptive resonance theory (ART) possesses an answer to all these questions.

5.2 Adaptive resonance theory Networks

Adaptive resonance theory (ART) networks are self-organizing neural networks. They follow both supervised and unsupervised algorithms. The basic ART system is unsupervised learning model. It consists of a comparison field and a recognition field containing neurons, a vigilance parameter, and a reset module.

5.2.1 Comparison field

The comparison field takes an input vector which is a one-dimensional array of values and shifts the input vector to a best match in the recognition field. The best match is the neuron whose weight vector most closely resembles the input vector.

5.2.2 Recognition field

Every neuron in the recognition field outputs a negative signal which is proportional to the corresponding quality of match to the input vector. This signal is sent to each of the other neurons in the recognition field and their output is inhibited accordingly. Thus they exhibit lateral inhibition, where each neuron represents a category to which input vectors are classified.

5.2.3 Vigilance parameter

After the process of classification of input vectors is performed, the reset module compares the strength of the match to the vigilance parameter which has considerable influence on the system. Higher vigilance produces many fine grained categories. Lower vigilance results in fewer more general categories.

5.2.4 Reset Module

The main function of the reset module is to compare the strength of the recognition field and the vigilance parameter. If the threshold value is satisfied, then the training commences. Else, if the match doesn't meet the vigilance parameter, then the firing recognition neuron is inhibited until a new input vector is applied. Training commences only upon the completion of the search procedure where the recognition neurons are disabled one by one by the reset function until the vigilance parameter is satisfied by a recognition match. If there is no match, then they are adjusted towards the matching input vector.

6. Conclusion

Since the other artificial neural networks suffer from plasticity stability dilemma, it would be more efficient to use Adaptive Resonance networks for the purpose of surveillance since it provides more quality and robustness in object detection.

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