Semisupervised Learning and Special Coding Based on Hebbian Ensemble Neural Network

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Abstract

Supervised learning as a rule demands to mark off the objects in the images and to give them the names before beginning the training process. Semisupervised learning process starts from the image clustering and only after that the names are assigned to the clusters that correspond to different objects. Semisupervised learning permits minimization of the time needed to prepare image databases for training process. In this paper we propose to use Hebbian ensemble neural networks for image clustering and further information coding. We suppose that this method will be useful for face recognition, texture recognition, handwritten text recognition and some other pattern recognition tasks

1. Introduction

In our previous works we used the name “Ensemble Neural Network” to denote the artificial neural network that contains Hebbian neural ensembles, i.e. subsets of the neurons that have connections between each other with synaptic weights much higher than average value of synaptic weights in the neural network.

At present the term “Ensemble Neural Network” frequently is used for a group of different neural networks that collaborates to solve common task (for example, pattern recognition). For this reason we will call our networks “Hebbian Ensemble Neural Networks”. This type of neural networks was proposed by D.O.Hebb in [1]. D.O.Hebb supposed that each concept may be presented in neural network not by single neuron (as output neuron that corresponds to recognized class in neural classifier, for example) but by a subset of neurons that forms neural ensemble. When a part of Hebbian neural ensemble is excited, the excitation spreads on the whole ensemble. Though Hebbian ensemble consists of many neurons it behaves as a single information unit. Hebbian ensembles can have intersections. So each neuron can belong to many ensembles. This peculiarity generates the whole network excitation problem when initially only one ensemble is excited. This problem can be solved by simulation of attention mechanisms [2], [3].

Many authors (e.g., [4] - [10]) analyzed the properties of Hebbian ensembles using mathematical methods or computer simulations, but not so much attention was paid to practical applications of this paradigm. In this article we propose to apply Hebbian ensemble neural network for semisupervised learning in the image recognition tasks.

2. Hebbian ensemble neural network

The scheme of Hebbian ensemble neural network is presented in Fig. 1. The scheme of the Hebbian ensemble neural network consists of input neurons, synaptic weight matrix and output neurons (Fig.1).

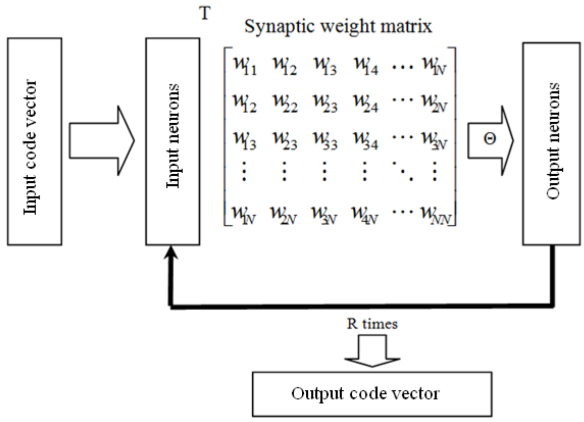

Figure 1: The scheme of Hebbian ensemble neural network.

Input neurons are latches that store the value of input code vector. Output neurons sum up the signals of input neurons multiplied with synaptic weights and perform threshold function to produce binary output vector.

$$y_i = f(\sum_{j=1}^{N} w_{ji} \cdot x_j), \qquad (1)$$

where $f()=1$, if $\sum_{j=1}^{N} w_{ji} \cdot x_j \geq \theta$,

$f()=0$, if $\sum_{j=1}^{N} w_{ji} \cdot x_j < \theta$,

where x_j is the binary output value of the *j*-th input neuron, y_i is the binary output value of the *i*-th, θ is the output neuron threshold. The threshold θ is the same for all output neurons. Its value is calculated by special algorithm in each cycle of neural network recalculation. The threshold is selected to achieve the number of active neurons close to the constant value *m* that is given for the neuron network as a parameter. As a rule the threshold value is larger for larger synaptic weights between ensemble neurons. The threshold value can be used to estimate "how strong" ensemble is excited at the moment.

3. FRAV2D image database

In this article we describe the application of Hebbian ensemble neural network for the problem of object detection in the image. We use FRAV2D image database that was collected and developed in Rey Juan Carlos University, Madrid, Spain [11]. The FRAV2D image database contains 1696 images: 16 different images for each person, in total the database contains images of 106 persons. 16 different images correspond to expressions of different emotional states, different head inclination to the left, to the right, and so on. One example of the FRAV2D image database is presented in Fig.2.

We suppose that Hebbian ensemble neural network will be capable to find the objects as eyes, nose, and mouth without preliminary marking them on the images.

Preliminary processing of the images includes correction of mean brightness and filtration with high spatial frequencies filters.

After preliminary processing it is possible to start the program of Hebbian ensembles formation. For this purpose we use relatively small window (Fig. 2), that scans the image and produces the binary code of the image part that appears in the window. The size of the window should be selected as follows: the internal space of the window has to include the whole object or the major part of the object to be found. If we expect to recognize the objects of different sizes, various windows should be selected, and the image should be sequentially scanned several times.

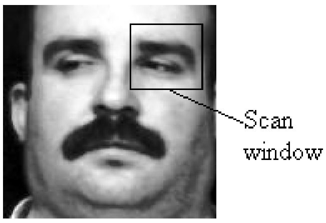

Figure 2: Scan window in image from FRAV2D

4. Image coding

The scheme of image part coding in the window is shown in Fig.3. It works as follows: preprocessed image is scanned by the window and for each position of the window feature extractor FE finds the specific features in the window. Different types of feature extractors can be used. In this work we use feature extractor from PCNC (Permutation Coding Neural Classifier [12]). To use this feature extractor we consider the scan window as a whole image and create smaller window that is moved within scan image to provide the information for encoder ENC (Fig.3). Encoder produces binary code that is used for Hebbian ensembles formation.

The Hebbian ensembles can be used to find the similarity of different objects. If scan window finds two images that produce code vectors with many equal components, the synaptic weights between neurons that correspond to these components grow up. The Hebbian ensemble corresponding to similar images starts to appear. If similar images are found many times, corresponding synaptic weights achieve values much larger than the mean values of synaptic weights in the matrix. It means that the Hebbian ensemble is formed for the group of similar images.

At the first stage of semisupervised learning the scan window looks through all images of the training database and the synaptic weight matrix is corrected in each position of the scan window. For this purpose the following equation is used:

$$w_{ij}(t+1) = w_{ij}(t) + 1 \text{ , } \mathbf{if} \ ((v_i = 1) \ \& \ (v_j = 1)), \qquad (2)$$

where $w_{ij}(t+1)$ is the value of synaptic matrix component after correction, $w_{ij}(t+1)$ is the value of synaptic matrix component before correction, v_i is the i-th component of the binary code vector that appears at the output of the encoder ENC (Fig.3), v_j is the j-th component of the code vector.

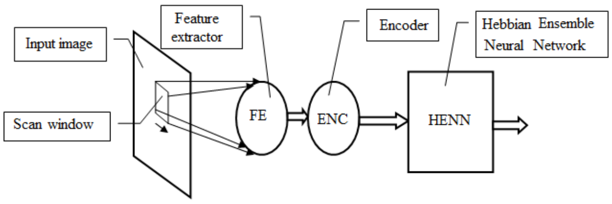

Figure 3: Image coding

When all images of the training database are scanned we have the Hebbian ensembles that correspond to different objects that were found in the images. Now it is necessary to give the names to the ensembles using the names of corresponding objects. For this purpose it is necessary to prepare the code vectors of the names. For each class of the objects that can be found in the image we prepare a random binary vector that will serve as the name of this class.

When all the names are created the second stage of semisupervised learning is started. The training database is scanned secondly. In each position of the scan window after coding of input information Hebbian ensemble neural network is recalculated according to the equation (1) and the threshold value θ is selected to obtain approximately m active neurons at the output. If the value θ is low, no Hebbian ensemble corresponds to the window position. If the value θ is high, the supervisor (operator) looks at the image and selects the name of the object that appears in the scan window. If one of the created names is good for the scan window image, the binary code vector of the name is added to the code vector of excited ensemble, and correction of synaptic weights is made according to the equation (2). The code of the name contains less than m active neurons, but these active neurons repeatedly appear in each example of the ensemble that corresponds to the objects with the same name.

Hebbian ensembles have relatively complex internal structure. As a rule a part of the ensemble neurons has very strong synaptic connections between them. This part is termed "nucleus". The neurons of the nucleus are excited always when initially was excited any part of the ensemble. Other parts of the ensemble belong to the "fringe". Real image determines what part of the fringe will be excited in each case. In our system the name of the object corresponds to the "nucleus" of the ensemble.

When we apply this network to the test database, the neurons corresponding to the names of the objects will appear when the system will "see" the object in scan window, i.e. the system will recognize the objects.

5. Discussion

The Hebbian ensemble neural network permits us to work with unmarked image databases for semisupervised learning. Semisupervised learning starts from the Hebbian ensemble formation. These ensembles include feature combinations that frequently appear in corresponding objects.

After ensemble formation the operator gives the object names to the corresponding ensembles. This process demands much of work at the initial stage. Little by little the system begins to recognize the names of the objects, and operator has to correct it only when the system makes the error. For large image databases this process will demand less work than the mark up process for supervised learning.

6. Conclusions

The Hebbian ensemble neural network is proposed for semisupervised learning. The learning process begins from automatic formation of the neural ensembles that correspond to the images of different objects. At the second stage of semisupervised learning operator gives the names of the objects to the neural ensembles that were formed previously. This type of learning will be used for very large image databases that are difficult to mark up.

7. Acknowledgements

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