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USING NEURAL NETWOKS FOR GEOMETRICAL SHAPES RECOGNITION

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Abstract*: The work displays models of graphical objects recognition systems using Hamming network and linear network with three layers as recognition modules. It represents results of learning speed estimation, tests of capability and graphical objects recognition efficiency when using two mentioned methods.*
Keywords*: graphical objects recognition, Hamming neural networks*

Introduction

Building an automatical handwriting recognition system requires development of computer systems that have the ability to detect and recognize graphical images of the handwritten symbols. The complexity of the task is caused by ambiguity of detecting separate symbols and by the variety of symbol class representatives. Symbols that were localized can be normalized to some extend by applying the transformations of scaling and rotation. But even after normalization of the symbol is complete variety of image shapes is rather significant. Additional difficulty is brought by noise appearance caused by introducing low quality images containing text that were captured by scanner or camera. In such situations usual minimax recognition methods give unsatisfactory results. In conditions of limited information and high noise level neural networks software technologies may become much more efficient. Neural networks methods are convenient because the procedure of preliminary image processing is much simplified for them and also because of using the values of two-dimensional color function as a feature vector. This work discovers the possibility of using several neural networks models for handwritten symbols recognition.

Hopfield neural networks

Using Hopfield neural networks in the learning process one needs to input one correct symbol sample of each class. Image feature vector is built according to the next rule. The learning sequence symbol localization rectangle (fig .1, first column symbols) that has 20x20 size after normalizing is scanned by rows. Black color point corresponds to the feature vector component value of "1", white color point - to the value of "-1". Neuron synapse weight coefficients matrix has dimensions of 400x400 and reflects the associative links between the image points [1].

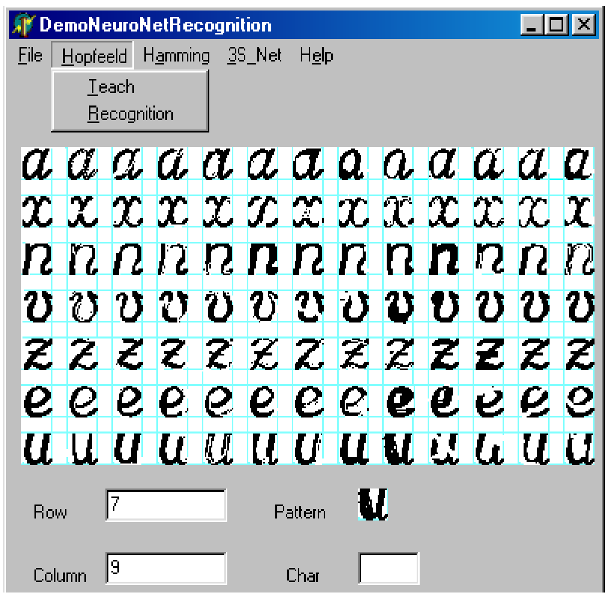

Figure1.

While recognizing the unknown symbol its graphical image, as well as during the learning stage, is replaced with according feature vector. During the analysis process neural network chooses the sample that is the most associated with the unknown symbol or stabilizes to the unknown symbol. Thus Hopfield neural network doesn't allow to select the class for each symbol directly but only replaces the initial image of the unknown symbol obtained on input with some sample symbol image or undefined image. Defining the recognized class requires additional procedure of two images comparing.
The biggest disadvantage of Hopfield neural networks is a large size of synapse link matrix.

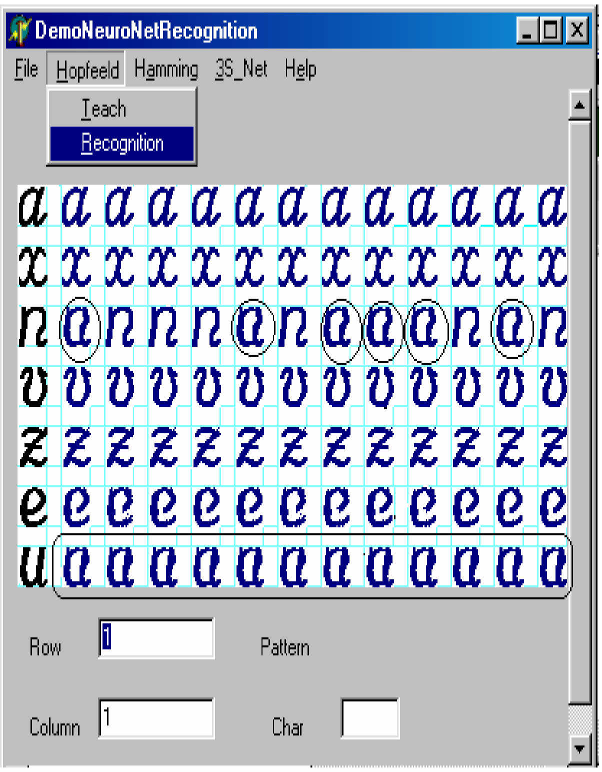

Figure 2.

The method gives indefinite results if the symbols have similar geometrical structure (fig. 2). In some cases the output images correspond to "corrupted" sample images (fig.2, "z", "e"). The need of large amount of feature vector components (6-7 different features on each symbol class) both with the small size of letters requirement significantly limits the size of the acceptable alphabet.

Hamming neural networks

Hamming neural network [1,2] tend to correspond to the classic symbol recognition task interpretation, i.e. based on a graphical image it defines the alphabet symbol or its alphabet order number. Symbol image is replaced with an appropriate feature vector as well as for the Hopfield network. Network consists of two neural layers. Each layer consists of M neurons, where M is a number of classes. First layer neurons have synaptic links with each component of the input feature vector and second layer neurons have synaptic links with each network output element.

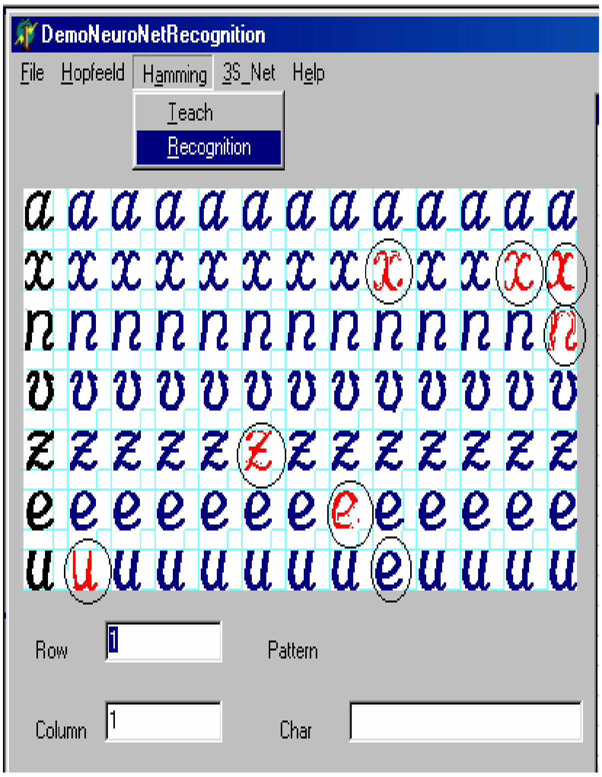

Figure 3.

Synapse coefficients matrix of the first layer has a dimension of Mx400, where M is a number of classes and synapse coefficients of the second layer are constant. During samples feature vector processing only first layer synapse coefficients are calculated. The learning sequence contains one sample of each alphabet symbol in the order of their alphabet appearance.
Neural network reaches higher effectiveness if

each class corresponds to some defined binary output. Then during the recognition process the unknown symbol class is defined uniquely by the index of active output element. Since the values of the threshold function for neural elements activation are calculated with the empirical method incorrect threshold value selection can result in stabilization of the input vector with only zero components or with some components not equal to zero. Such situations are treated as errors of recognition (fig. 3).
Despite having more complex structure Hamming neural network requires less processing resources than Hopfield network along with having higher recognition quality. Besides, Hamming neural network allows defining a class of the recognized symbol directly without any additional checking.

Three-layered neural networks with the back propagation of error

Multi layer neural networks are more steadfast to deformations and scaling transformations. Three-layered neural network consists of an input layer, each neuron for each feature vector component (feature vector values are calculated in the same way as in the previous cases), intermediate and output layers that have sizes equal to a number of alphabet symbols.
Learning is controlled by a "teacher" using the back propagation of error principle.
The process of learning with the random sample selection is going on until the number of errors is stabilized. Multilayer neural networks have better recognition parameters and thus better reliability and speed (of one directed signal transferring inside the network). But this result is gained with a complicated neural network structure and quite complicated iteration learning process.

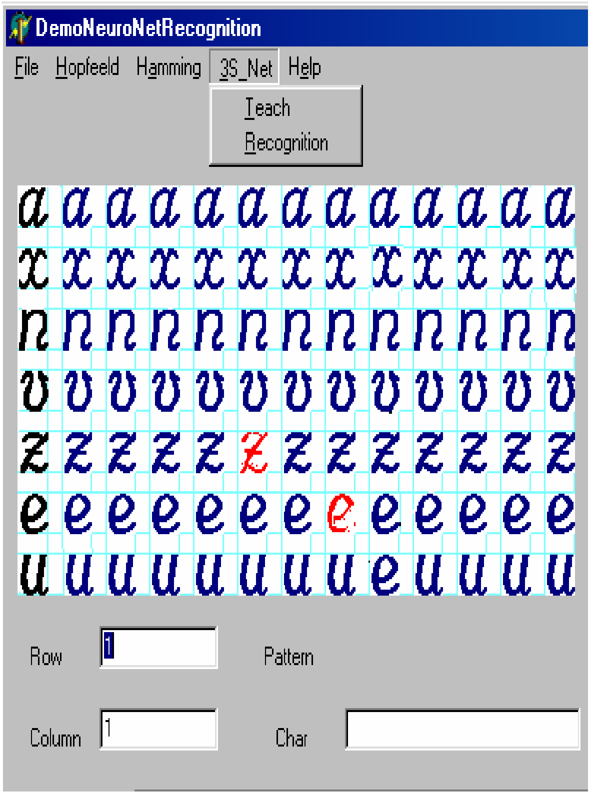

Figure 4

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