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Traffic Infrastructure
Preliminary Communication
U. D. C.: 656.851
Accepted: Oct. 30, 2000.
Approved: Dec. 12, 2001.

NEURAL NETWORK FOR RECOGNITION OF COUNTY CENTRE POST CODES

ABSTRACT

The work represents an artificial neural network for recognition of county centre post codes. The neural network POSTKLAS serves as the classification system for the sorting of two-digit address data. The developed model represents a two-layer network which learns by using backpropagation algorithm. The method of address data recording in the model has been presented. By analysing the sorting results the possibility was determined of applying the developed neural network for recognition even in cases of distorted input patterns. The modelling was done by means of Matlab programming system.

KEY WORDS

routing of postal items, pattern recognition, neural networks

1. INTRODUCTION

When introducing machine routing and processing of postal items, attention should be paid to the method of writing addresses so as to enable correct recognition and routing. For faster processing of the postal item itself, the addresses usually include the number of the destination post office. Regardless of the size of the space reserved for entering the post code, it depends on:

- type of input: whether the number is entered by machine or manually,
- font,
- method of entering the digits (italic or regular),
- whether the digits are written in bold,
- colour of the entered digits, etc.

The basis of the advanced machine processing of postal items, e.g. SARPP - Automatic Letter Sorting System made by Siemens, used by the HP – Croatian Post, represents a module of machine readable address data on postal items. Machine recognition of address data, which determines other working processes in handling mail, is the task performed by the recognition module.

2. CHARACTER RECOGNITION PROCESS

Machine recognition of address data entered manually or by machine (typewriter, printer) on the postal item consists of two processing phases:

- scanning,
- optical recognition of characters.

Scanning means that the postal item passes through the scanner which scans that part of the item which contains the address data necessary for subsequent routing. The obtained image is converted into the digital form and passed on to the character recognition module.

Optical recognition of characters means that the software for optical recognition of characters analyses the digitised group image with all the recorded characters onto the digitised images of every single character (characters include letters, digits, hyphens, periods, commas, etc.) The isolated single characters are compared under the program control with the characters contained in the database. The recognition process is completed when the recognised address data on the item match the address data from the database. If the program cannot determine the match, the image of the scanned address data is forwarded to the video-coding terminals where the operator enters the necessary data into the computer by means of a keyboard. Successful processing of address data (reading, entering) starts the process in which address data are assigned adequate address code which will be printed on the postal item in the form of a barcode.

During the scanning procedure, the image is divided into image elements. Depending on the intensity (single-colour images) or colour and position, the image elements are assigned adequate binary values in the scanner video memory.

The digitised image is represented by binary values of the image elements. The more bits are used for one pixel (greater possibility of analysing an image of various nuances), the more reliable the image reproduction. Thus, e.g. for the representation of a black and white image, one bit will be sufficient (0 for black and 1 for white). The usage of e.g. 8 bits will suffice to represent an image consisting of 256 different levels of grey. By obtaining the scanned digital image of adequate values and positions of image elements, the images can be reconstructed on the monitor or printed by the printer.

The scanned image can be reconstructed by the computer, but the data contained in the image (such as e.g. address data) cannot be individually used and processed by the computer. For that purpose, the scanned characters have to be assigned adequate standard coded characters, such as e.g. ASCII code characters. In that form the keyboard enters every keyed-in character into the computer. The conversion of the characters entered by intensity and position into ASCII characters is called optical recognition of characters. The conversion is done by the character recognition program. The task of the character recognition program is to decompose the image containing characters into single characters, and to determine on the basis of location and amount of pixels which ASCII code matches the scanned character. This is achieved by comparison of the position of all pixels of every scanned character with the position of pixels of characters entered into the database. When a matching character is found in the database, then the scanned character is converted into the ASCII character.

The comparison of digitised character with the character from the database is based on one of the two methods:

- complete image of the scanned character in pixels is compared to the pixels of characters in the database, until a matching character is found,
- the scanned character is divided into several characteristic elements (straight lines, arches, circles, ellipses etc.) and then these elements, i.e. their orientation (horizontal, vertical, slanted) and position (on top, in the middle, or at the bottom of the character) are compared with the adequate elements of the characters contained in the database, until a matching character is found in the database, which consists also of elements with identical characteristics.

Recognition of characters is relatively easy when the characters had been entered by a typewriter or a printer. Since these are mainly standardised forms of characters, the program needs to be able to recognise characters entered in as many different forms as possible. If the colour of the character is sufficiently distinguished from the background, the success of recognising machine-written characters can be fairly high. The more details and various methods of writing a character are contained in the database, the more successful the recognition of alphanumeric characters. However, it needs to be noted that searching the database may be time-consuming so that a balance has to be found between a wish to have a very detailed (very comprehensive) database and the wish to save time when searching the database.

The recognition procedure will be more efficient if it is performed in a well-known environment, i.e. in which the allowed shapes of characters are limited. A good example is the recognition of address data on postal items. To eliminate doubts regarding the character contained within address data, all characters within one logical unit (e.g. post code) are compared with adequate unit from the database. Also, several logical units (e.g. number and name of the destination post office) are compared with such units in the database. In this way impossible assumptions can be eliminated (e.g. post code which does not exist or a non-existing combination of post code number and name of the destination post office).

For machine reading of address data in the automatic handling systems of postal items, it is important for maximum efficiency (speed and accuracy) in handling a huge number of postal items to insure conditions for undisturbed operation of the scanner and the character recognition program.

Although postal items are transported through the system at high speeds (the speed of letters ranges between 3 – 5 m/s, parcels from 1 – 2 m/s), the average efficiency of recognising machine-written address data amounts to about 95 percent, and of manually written data about 65 percent. Today, the ratio between machine and manually written addresses is about 17:3.

3. RECOGNITION OF COUNTY CENTRE POST CODES BY MEANS OF NEURAL NETWORK

For machine routing of letters a model of artificial neural network POSTKLAS has been developed for the recognition of address data of the postal item.

The adequacy of applying the artificial neural network in the process of recognising the characters, including address data, lies in the capability of establishing the dependence between the features of the input-output pairs of characters in the learning process and the possibility of recognising the characters in the network exploitation process. The behaviour of the artificial neural network in the learning process as well as in the application process reminds of the behaviour

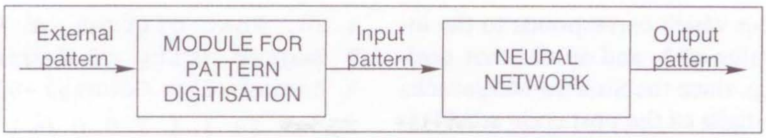

Figure 1 - Sustav za prepoznavanje adresnih podataka

of a biological neural network, e.g. the capability of example-based learning, capability of generalising, capability of recognition, etc.

Artificial neural network consists of a number of interrelated elementary processing units, artificial neurones, distributed into layers. The artificial neurone reminds of a biologic neurone and consists of dendrites, nuclei and axon. The neurone receives signals through dendrites from the neurones connected to it. The signals are processed in the nucleus, and axon transmits the processed signals to other neurones in the network. In case of character recognition, image elements are assigned to neurone located at the network input and output.

Neural network can contain several layers, and the adequacy of applying multi-layer networks lies in the possibility of modelling an arbitrary practically usable function.

3.1. Address data recognition system

The address data recognition system consists of a subsystem for image inputting and processing and a subsystem for recognising. The recognition capabilities provided by the artificial neural network are used for recognition, Figure 1.

According to the territorial organisation of the counties in the Republic of Croatia with a total of twenty counties, the post offices are assigned adequate post codes.

The developed neural network recognises 20 numbers of the county centres (the first two digits of the post office) which is digitised by the subsystem for image inputting and processing (video camera or black and white scanner) and presented by image elements, binary digits, in a matrix containing 7 rows and 10 columns. The digitised two-digit figure at the neural network input is presented in Figure 2. The patterns of 20 county centre numbers are recorded so that the digit entered into the space reserved for entering the post code is presented in the matrix form, thus simplifying the machine readability, recognition and routing of the postal item.

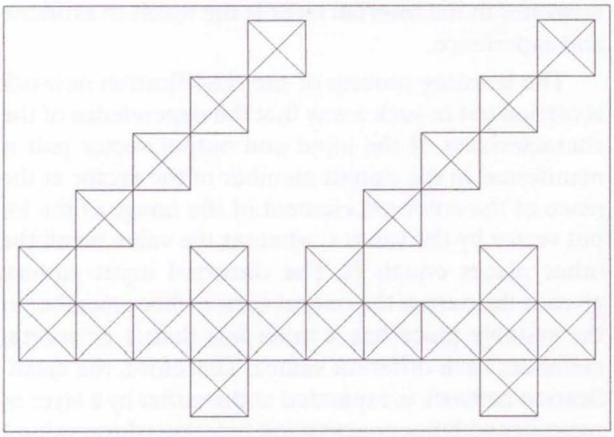

Figure 2 - Undistorted digits of a two-digit number

Due to the imprecision of the subsystem for image inputting and processing, taking into consideration the actual conditions which might arise in the recognition process, the first two digits of the router at the neural network input may be distorted, i.e. there may be noise interference.

Following the learning phase, the neural network should be able to recognise the pair of input digits even when the digits contained in the pair are distorted, Figure 3. The neural network must correctly recognise the undistorted digits and provide good recognition of the distorted digits assigned to input process units of the developed artificial neural network.

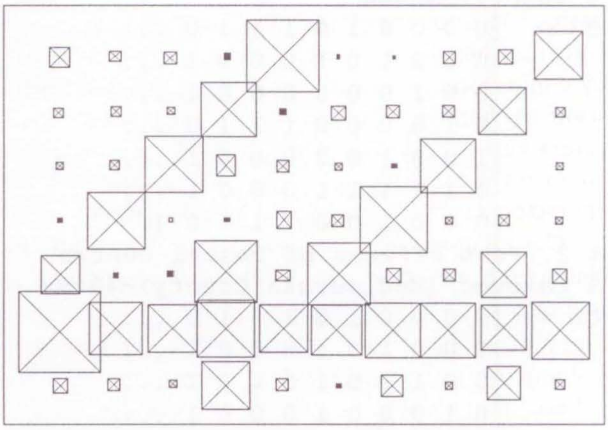

Figure 3 - Distorted digits of a two-digit number

3.2. Presentation of input and target patterns

Two-digit numbers of the county centres as input and output patterns are recorded in the form of vectors, because of the recognition suitability by the program version of the neural network. The length of each of the 20 vectors is 70 (= 7*10) elements. The value of a single element corresponds to the binary value of the digitised digit. The value at a certain position equals 1, if a coloured element of the image (pixel) is at the given position of the digitised image. Otherwise, the value equals 0. The target vector at the position of the member which corresponds to the input pattern has the value of 1, and at all other positions the value is 0. E.g. since the Sisačko-Moslavačka County (the first two digits of the post code are 44) is at the 12th position in the alphabetical directory of the counties, in the target vector it has the value of 1 only on the 12th position, and on all the other positions the value 0 is entered. The following is an overview of setting the input and target vectors, expressed by instructions of the program system Matlab:

```
% SETTING THE INPUT AND TARGET
% PATTERNS
% Record of the input group of
% two-digit numbers of county centres
% (matrix 7*10 presented by vector of
% length 70)
% Numbers of post offices in the
% alphabetic order of the counties
% Copyright (c) 1992-93 by the
% MathWorks, Inc.
% Adapted to the needs of the
% POSTKLAS model by: H.Gold, 1997,
% M.Samodol, 2000.

% 1. Post offices of Postal centre
% Bjelovar (Bjelovarsko-Bilogorska
% County)-43xxx
BJ =  [0 0 0 0 1 0 1 1 1 0 ...
       0 0 0 1 0 1 0 0 0 1 ...
       0 0 1 0 0 0 0 0 0 1 ...
       0 1 0 0 0 0 1 1 1 0 ...
       1 0 0 1 0 0 0 0 0 1 ...
       1 1 1 1 1 1 0 0 0 1 ...
       0 0 0 1 0 0 1 1 1 0 ];
% 2. Post offices of Postal centre
% Čakovec (Međimurska County)-40xxx
CK =  [0 0 0 0 1 0 1 1 1 0 ...
       0 0 0 1 0 1 0 0 0 1 ...
       0 0 1 0 0 1 0 0 0 1 ...
       0 1 0 0 0 1 0 0 0 1 ...
       1 0 0 1 0 1 0 0 0 1 ...
       1 1 1 1 1 1 0 0 0 1 ...
       0 0 0 1 0 0 1 1 1 0 ];
..............................
% 12. Post offices of Postal centre
% Sisak (Sisačko-Moslavačka
% County)-44xxx
SK =  [0 0 0 0 1 0 0 0 0 1 ...
       0 0 0 1 0 0 0 0 1 0 ...
       0 0 1 0 0 0 0 1 0 0 ...
       0 1 0 0 0 0 1 0 0 0 ...
       1 0 0 1 0 1 0 0 1 0 ...
       1 1 1 1 1 1 1 1 1 1 ...
       0 0 0 1 0 0 0 0 1 0 ];
..............................
% 20. Post offices of Postal centre
% Zagreb (City of Zagreb and
% Zagrebačka County)-01xxx
ZG =  [0 1 1 1 0 0 0 1 1 0 ...
       1 0 0 0 1 0 1 0 1 0 ...
       1 0 0 0 1 1 0 0 1 0 ...
       1 0 0 0 1 0 0 0 1 0 ...
       1 0 0 0 1 0 0 0 1 0 ...
       1 0 0 0 0 1 0 0 1 0 ...
       0 1 1 1 0 0 0 0 1 0 ];

% Vector of input postal codes
alphabet =
  [BJ,CK,DU,GO,KA,KO,KR,OS,PA,PO,RI,
   SK,SB,ST,SI,VA,VI,VT,ZD,ZG];
% Matrix of output values (identity
% matrix)
% Record of target patterns presented
% by vector of 20 elements.
% Element of target vector which
% corresponds to the i-th input code
% equals 1,
% other elements equal 0.
targets = eye(20);
```

3.3. Classification network

The neural network for sorting of two-digit numbers of post offices is a two-layer network composed of 70 input neurones, 10 neurones with logistic activation function in the internal layer and 20 neurones with logistic activation function in the output layer, Figure 4 - Matrix W and vector B correspond to the weights and bias elements.

Logistic activation function has been selected due to its suitability for learning of patterns composed of binary values. The selection of the number of neurones in the internal layer is the result of estimate and experience.

The learning process of the classification network is carried out in such a way that the dependence of the characteristics of the input and output vector pair is manifested in the output member of the vector at the place of the coloured element of the image of the input vector by the value 1, whereas the value on all the other places equals 0. The distorted input pattern gives at the output the output vector whose member at the suitable place has a value less than 1 or several members have different values. Therefore, the classification network is expanded at the outlet by a layer of neurones with linear activation function whose value 1 is assigned to the element that has a greater value.

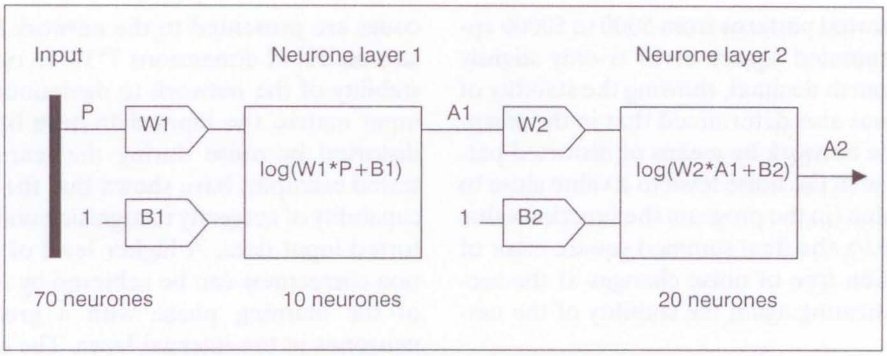

Figure 4 - Neural network for sorting of postal codes

3.4. The learning process of the classification network

For the learning process, undistorted and distorted input patterns are used. During the learning period, the network uses the error backpropagation algorithm with flexible learning coefficient and learning moment.

The network learns by patterns free of noise in 5,000 epochs, i.e. while the sum of the square errors was less than the value 0.1. The values of weights among neurones as well as between neurones and the additional member are stored after having been taught in four files (prl_w1.dat, prl_w.dat, prl_b1.dat and prl_b2.dat).

The network then learns by groups of 10 input patterns without and with noise in 300 epochs, i.e. as long as the sum of square errors is less than 0.6. The amount of the permitted error is increased so that the network can learn to respond correctly to the majority of patterns free of distortion as well as to those with distortion. In this way the network learns to recognise also the distorted patterns.

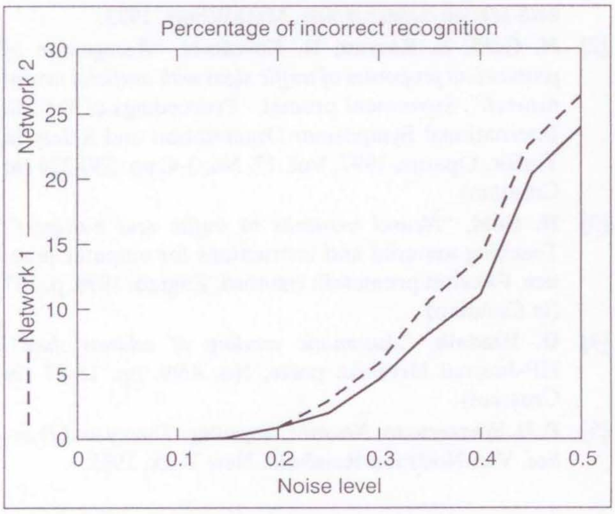

Figure 5 - Percentage of incorrect pattern recognition in POSTKLAS model depending on the noise level: a) in case of learning without noise (Network 1) and b) in case of learning with noise (Network 2).

Based on the previous learning process, the network recognises correctly patterns with relatively quite a lot of noise compared to the exact recognition of patters without noise. Therefore, additional learning is carried out with input patterns without noise. In order to increase the number of recognised patterns free of distortion at the network input, additional learning was carried out with the undistorted input patterns. After this learning process, the values of weights between neurones are stored in four new files (prw_w1.dat, pr2_w2.dat, pr2_b1.dat and pr2_b2.dat). The network uses the weight values from the four mentioned files in the procedure of classifying the two-digit address data.

4. ANALYSIS OF THE ACCURACY OF CLASSIFICATION NETWORK OPERATION

In analysing the capability of recognising address data the network is presented with input patterns with various degrees of distortion.

Analysis has been carried out so that from the input set of two-digit numbers the network is presented with randomly selected 100 patterns to which in certain testing iterations the noise values are superimposed. The selected values of noise level range between 0 and 0.5, where 0 refers to the minimal, and the value 0.5 to the maximal noise level. With a certain level of superimposed noise, the values of the output vector are calculated. Linear activation function is then applied to the values of the output vector elements. After the processing has been completed, the network activates only one of 20 elements of the output vector. The position of the selected element corresponds at the network input to the presented two-digit number of the post office. In case of incorrect classification, the counter of incorrect classifications is increased by 1, and for the given noise level calculates the percentage of incorrect classifications, Figure 5.

During the analysis it was determined that the increase of the number of iterations in teaching the network with undistorted patterns from 5000 to 50000 epochs, the final summed square error is only slightly changed at the fourth decimal, showing the stability of the network. It was also determined that in the learning process of the network by means of distorted patterns, the increase in the noise level to a value close to the maximum value (in the program the function value random equals 0.9), the final summed square error of pattern recognition free of noise changes at the second decimal, indicating again the stability of the network.

4.1. Application of neural network model - POSTKLAS

An example of applying the POSTKLAS model in case of classification of the address data is the procedure for recognising the post code of the Sisačko-Moslavačka County. During the learning phase, and according to previously mentioned protocols, the neural network is presented with postal codes with undistorted and distorted digits for all the twenty counties. During the usage phase, the network is presented at the input with a distorted code of the county centre. For the given input pattern, the network responds with a graphical presentation of the made classification. The distorted input pattern with noise level 0.2 for the example of the post office number of the Sisačko-Moslavačka County, that is the code 44, as well as the network response are presented in Figure 3 and Figure 2.

Program module instructions for teaching, checking the recognition correctness, checking the recognition accuracy, and the graphical presentation of the two-digit address data can be found in the appendix.

5. CONCLUSION

The procedure of routing postal items using automatic processing machine is based on the recognition of address data. The address data can be recorded manually or by machine using various types of characters and ways of recording.

Artificial neural networks show the capability of recognising after having learned on a given set of data. For the needs of recognising postal address data, a two-layer neural network POSTKLAS was developed, which learns by means of error backpropagation algorithm. The network is intended for the recognition of two-digit postal codes of county centres. The postal codes are presented to the network in digitised form as a matrix of dimensions 7*10. In order to check the stability of the network to deviations from the given input matrix, the input data have been intentionally distorted by noise during the learning phase. The tested examples have shown that the network has the capability of correctly recognising undistorted and distorted input data. A higher level of pattern recognition correctness can be achieved by a longer duration of the learning phase with a greater number of neurones in the internal layer. The discrimination of the input patterns is achieved by increasing the input matrix. The model of the neural network for recognition of the address postal code of the county centre has been developed by means of the program package Matlab.

SAŽETAK

NEURONSKA MREŽA ZA PREPOZNAVANJE ADRESNOG POŠTANSKOG BROJA ŽUPANIJSKOG SREDIŠTA

U radu je predstavljena umjetna neuronska mreža za prepoznavanje poštanskog broja županijskog središta. Neuronska mreža POSTKLAS služi kao klasifikacijski sustav za razvrstavanje dvoznamenkastih adresnih podataka. Razvijeni model predstavlja dvoslojnu mrežu koja uči korištenjem algoritma s povratnim rasprostiranjem pogreške (backpropagation algorithm). Predstavljen je način zapisa adresnih podataka u modelu. Analizom rezultata razvrstavanja utvrđena je mogućnost primjene razvijene neuronske mreže za prepoznavanje i u slučajevima oštećenih ulaznih uzoraka. Modeliranje je izvedeno korištenjem programskog sustava Matlab.

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APPENDICES

P1. Program for network teaching module

```
% POSTKLAS P1
% TRAINING OF NEURAL NETWORK TO RECOGNISE POSTAL CODE OF COUNTY CENTRES
% The two-layer neural network is trained with logistic activation
% function of neurone in internal and output layer. The network has 70
% input (distributive), 10 internal and 20 output neurones.
% The first teaching of the network is performed with input patterns (postal
% codes) without noise. Then the network learns with patterns with noise.
% Finally, it is again trained with patterns without noise. The trained
% neural network classifies correctly patterns without noise, and very well
% those with noise.
% Copyright (c) 1992-93 by the MathWorks, Inc.
% Adapted to the needs of the POSTKLAS model by: H.Gold, 1997, M.Samodol,
  2000.

% PREPARATION OF CODES
hpprob;

% SETTING THE NETWORK ARCHITECTURE
[R,Q] = size(alphabet); S1 = 10; [S2,Q] = size(targets);
[W1,B1] = nwlog(S1,R);W2 = rands(S2,S1)*0.01;
B2 = rands(S2,1)*0.01;

% INPUT OUTPUT PATTERNS
P = alphabet;
T = targets;

% NETWORK TRAINING PARAMETERS
disp_freq = 20;
max_epoch = 5000;
err_goal = 0.1;
lr = 0.01;
lr_inc = 1.05;
lr_dec = 0.7;
momentum = 0.95;
err_ratio = 1.04;

% NETWORK TRAINING BY PATTERNS WITHOUT NOISE (UNDISTORTED PATTERNS)
TP = [disp_freq max_epoch err_goal lr lr_inc lr_dec momentum err_ratio];
[W1,B1,W2,B2] = trainbpx(W1,B1,'logsig',W2,B2,'logsig',P,T,TP);

% SAVING OF THE TRAINED NETWORK WITH PATTERNS WITHOUT NOISE - SAVE W AND B
save pr1_w1.dat W1 /ascii /double
save pr1_b1.dat B1 /ascii /double
save pr1_w2.dat W2 /ascii /double
save pr1_b2.dat B2 /ascii /double

% TRAINING PARAMETERS
max_epoch = 300;
err_goal = 0.6;
TP = [disp_freq max_epoch err_goal lr lr_inc lr_dec momentum err_ratio];
```

```
% NETWORK TRAINING BY PATTERNS WITH NOISE (DISTORTED PATTERNS)
for pass = 1:10
  fprintf('Prolaz = %.0f\n',pass);
  P = [alphabet, alphabet, ...
       (alphabet + randn(R,Q)*0.1), ...
       (alphabet + randn(R,Q)*0.2)];
  T = [targets targets targets targets];

  [W1,B1,W2,B2] = trainbpx(W1,B1,'logsig',W2,B2,'logsig',P,T,TP);
  end

% INPUT OUTPUT PATTERNS
P = alphabet;
T = targets;

% TRAINING PARAMETERS
max_epoch = 5000;
err_goal = 0.1;

% RE-TRAINING OF NETWORK BY PATTERNS WITH NOISE - SAVING W AND B
TP = [disp_freq max_epoch err_goal lr lr_inc lr_dec momentum err_ratio];
[W1,B1,W2,B2] = trainbpx(W1,B1,'logsig',W2,B2,'logsig',P,T,TP);

% SAVING OF THE TRAINED NETWORK WITH PATTERNS WITH NOISE - SAVING W AND B
save pr2_w1.dat W1 /ascii /double
save pr2_b1.dat B1 /ascii /double
save pr2_w2.dat W2 /ascii /double
save pr2_b2.dat B2 /ascii /double

% PRINTING OF ERROR
A = logsig(W2*logsig(W1*P,B1),B2);
SSE = sumsqr(A-T);
fprintf('Final summed square error without noise: %g.\n',SSE);
```

P2. Program module for checking the accuracy of character recognition

```
% POSTKLAS P2
% CHECKING CORRECTNESS OF RECOGNITION OF POSTAL CODE OF COUNTY CENTRE
% Checking the capability of classifying the network which has been taught on
% recognising the first two digits of the postal code of the postal county
% centre with various noise levels in the input pattern.
% Results are presented of teaching the network expressed by the percentage
% of recognition error for cases of recognition of characters with and
% without noise.
% Copyright (c) 1992-93 by the MathWorks, Inc.
% Adapted to the needs of the POSTKLAS model by: H.Gold, 1997, M.Samodol,
% 2000.

% INPUT OUTPUT PATTERNS: alphabet, targets
hpprob;
[R,Q] = size(alphabet);
[S2,Q] = size(targets);

% NETWORK 1: NETWORK TRAINED BY PATTERNS WITHOUT NOISE
load pr1_w1.dat
load pr1_b1.dat
```

```
load pr1_w2.dat
load pr1_b2.dat

% NETWORK 2: NETWORK TRAINED BY PATTERNS WITH NOISE
load pr2_w1.dat
load pr2_b1.dat
load pr2_w2.dat
load pr2_b2.dat

% SETTING VARIABLES TO CHECK NETWORK FUNCTIONING
network1 = [];
network2 = [];

% SETTING PARAMETERS TO CHECK NETWORK FUNCTIONING
max_test = 100;
noise_range = 0:.05:.5;

% CHECKING NETWORK FUNCTIONING
for noiselevel = noise_range
  fprintf('Checking the network functioning with pattern noise level =
 %.2f.\n',noiselevel);
  errors1 = 0;
  errors2 = 0;
  for i=1:max_test
    P = alphabet + randn(R,Q)*noiselevel;

    % CHECKING NETWORK 1
    A = logsig(pr1_w2*logsig(pr1_w1*P,pr1_b1),pr1_b2);
    AA = compet(A);
    errors1 = errors1 + sum(sum(abs(AA-targets)))/2;

    % CHECKING NETWORK 2
    A = logsig(pr2_w2*logsig(pr2_w1*P,pr2_b1),pr2_b2);
    AA = compet(A);
    errors2 = errors2 + sum(sum(abs(AA-targets)))/2;
    end

  % RECORDING RESULTS
  network1 = [network1 errors1/max_test/Q];
  network2 = [network2 errors2/max_test/Q];
  end

% PRESENTING RESULTS
plot(noise_range,network1*100,'-',noise_range,network2*100);
title('Percentage of incorrect recognition');
xlabel('Noise level');
ylabel('Network 1 _ _   Network 2 ___');
```

P3. Program module for checking the accuracy of recognition

```
% POSTKLAS P3
% CHECK OF THE ACCURACY OF RECOGNISING POSTAL CODE OF THE COUNTY CENTRE
% Checking capability of classification of network using as example
% the postal code of the Sisačko-Moslavačka County.
% Copyright (c) 1992-93 by the MathWorks, Inc.
% Adapted to the needs of the POSTKLAS model by: H.Gold, 1997, M.Samodol,
```

```
% 2000.

% INPUT OUTPUT PATTERNS
hpprob; rand('normal');

% SETTING OF THE RESULTANT NETWORK
load pr2_w1.dat; load pr2_w2.dat; load pr2_b1.dat; load pr2_b2.dat;

disp('for display of input pattern with noise press any key!')
pause; disp('');

% PRESENTING OF THE DISTORTED POST CODE OF SISAČKO-MOSLAVAČKA COUNTY TO THE
% NETWORK
noisySK = alphabet(:,12)+rand(70,1)*0.2;
hsam(noisySK);
subplot(1,2,1)
A2 = logsig(pr2_w2*logsig(pr2_w1*noisySK,pr2_b1),pr2_b2);
answer = find(compet(A2) == 1);
disp(answer);pause;
disp('for display of recognised pattern press any key!')
pause; disp('');

% RESPONSE BY THE NETWORK TO THE INPUT PATTERN
hsam(alphabet(:, answer));
```

P4. Program module for graphic presentation of address data

```
function hsam(c)
% Plotting 70-member vector as matrix 7*10
% Copyright (c) 1992-93 by the MathWorks, Inc.
% Adapted to the needs of the POSTKLAS model by: H.Gold, 1997, M.Samodol,
% 2000.

x1 = [-0.5 -0.5 +0.5 +0.5 -0.5];
y1 = [-0.5 +0.5 +0.5 -0.5 -0.5];
x2 = [x1 +0.5 +0.5 -0.5];
y2 = [y1 +0.5 -0.5 +0.5];
clf reset
hold on
clf reset
plot(x1*11.6+4.6,y1*7.6+3.5,'m');
axis([-1.5 10.5 -0.5 7.5]);
axis('equal')
axis off
hold on
for i=1:length(c)
   x = rem(i-1,10)+0.5;
   y = 6-floor((i-1)/10)+0.5;
   plot(x2*c(i)+x,y2*c(i)+y);
end
hold off
```