Seed Quality Assessment Using Artificial Neural Networks

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Key Words: *Multidimensional vector classification; artificial neural networks; image processing; seeds.*

Abstract. *This paper discusses the possibility of seed quality assessment using artificial neural networks. We present a model of a classifier based on a cascade structure, which consists of different standard neural networks—LVQ networks and BPN. The classifier provides a precise classification of multidimensional vectors in classes with contacted boundaries. The classifier has an acceptable training resource. This problem is related to quality assessment of different products including seeds.In this paper the classifier is used for separation quality assessment based on geometrical parameters of corn seeds. These parameters are measured by a standard measurement method and a computer vision system. The results obtained by the proposed classifier are compared with results using the standard BP and RBF networks. If the seed dimensions are measured by the standard method the classifier gives a correct classification of all seeds. When the dimensions are measured by the computer vision system the classification accuracy is about 94.2%.*

I.Introduction

Quality assessment of agricultural products is a complex problem. The features of this products, which are used for quality classification, vary at wide ranges. On the other side, some of these features can not be measured precisely. In some cases features like shape, color, smell and taste are used for classification.

The seed quality is assessed by the following features: purity, homogeneity, germination, vigor, vitality etc. Because of features variety and the difficulties related to their estimation, technologies in this area have not pratically changed for many years. The expert with his knowledge and his abilities to interpret is a key figure in the process. This defines the nature of the assessment — subjective, slow and inaccurate.

The Development of an efficient automated technology for seed quality assessment supposes the following main steps:

— to form quantitative estimations of the features used as a basis for classification;

— to develop a formal model, which represents investigated objects as classification objects;

— to develop an appropriate classifier for grouping objects (seeds) into classes according to the standards.

Different features like form, size, color, surface texture, and typical elements (germ, fibrils etc.), are used for seed quality estimation [5,8,13,15,19]. Different sensors are used for measurement of these features: CCD cameras; X-ray sensors; sensors using reflection and passing of various radiations.

Multidimensional vector descriptors are used for formal presentation of seeds as classification objects. The morphological features, related to the shape and geometrical parameters of seeds [3,11,14,15], are used for purity analysis, germination, homogeneity, vigor and other similar sowing properties [12]. Color and texture features are used for authenticity, infection and germination assessment [10,5,6,7,8,16]. A combination of morphological and texture features is often used for improving of characteristics' informativity [8].

There are different principles and methods for seeds quality classification [3,17,18]. Some of the them are based on Artificial Neural Networks. [1,2,4,9,15,17]. Ruan and Ning [20] use BPN to determine roughness of wheat seeds infected with fusarium. Paliwal and Visen [17] use neural networks to identify some sorts of wheat crops. BPN is used by different authors to estimate various seed properties [4,9]. Aitkenhead and Dalgetty at al.[1] use neural networks for separation of wheat from weed seeds.

Apart from the encouraging results related to artificial neural networks applications in seed quality assessment, there are some problems:

— Large training sets are needed for an effective training of the neural network. (some training sets include hundred seeds).

— The number of inputs increases when the size of object vectors is bigger (this is necessary for more informative seed description). The training time (especially for frequently used BPN) increases when the number of inputs and the size of training sets grow. This leads to unacceptable resource requirements for neural network training.

— If there are classes with contacted boundary surfaces, a problem about classification of vectors lying near by boundary surfaces arises.

In this paper a new classifier is discussed based on different standard networks — LVQ and BP. This classifier has acceptable training resources and high classification accuracy.

2.Methods and Materials

2.1. The Seed Quality Assessment as a Problem of Multidimensional Vector Classification in Classes with Contacted Boundary Curfaces

The seed quality assessment is implemented by grouping seeds in classes based on several features. The Intervals for every feature x_i which define quality classes are: $\Delta_1 = x_i^1 \div x_i^2$; $\Delta_2 = x_i^2 \div x_i^3$; $\Delta_3 = x_i^3 \div x_i^4$ etc. They have contacted boundaries. A typical example of this task concerning corn seed classification on the base of shape and size is shown in *table 1*.

Table 1

№ class	Size and shape of grain	Height (X), Mm	Width (Y), Mm	Length (Z), Mm
First	Large round	5.5-7.5	8.5-9.5 (10)	-
Second	Large flat	3.5-5.5	8.5-9.5 (10)	до 11.0
Third	Middle flat	3.5-5.5	7.5-8.5	9.0-11.0
Fourth	Small flat	3.5-5.5	6.5-7.5	до 9
Fifth	Narrow flat	3.5-5.5	7.5-7.5	9.00-11.0
Sixth	Middle round	5.5-7.5	7.5-8.5	-

2.2. Application of Standard Neural Networks for Corn Seeds Separation

The most attractive network for this task is BPN (basic architecture or some variations). BP network presented in *figure1* is used for evaluation of corn seed separation in conformity with the data presented in *table 1*. Codes of the classes are given in *table 2*.

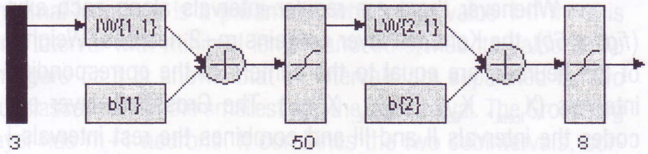

Figure 1. BP network

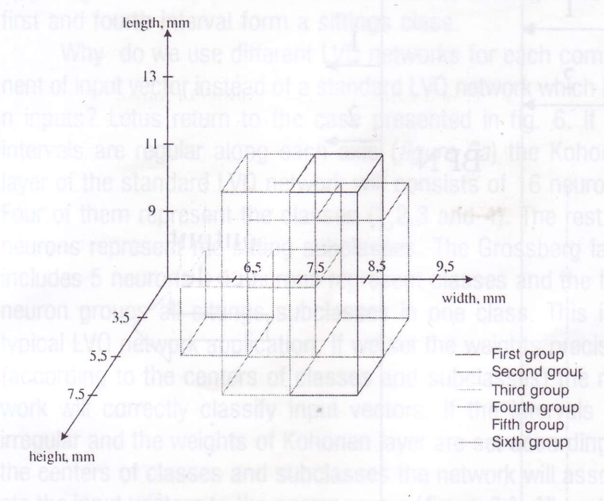

Figure 2. Seed class structure

All seeds which are out of specified range shown in *table 1* have to be grouped in a new class – sittings.

There are some problems using BPN:

1. Different classes have different dimensions along each co-ordinate axis (*figure 2*). This means that the classes centers will be irregularly distributed in the space of input vectors. It is expected that the input vectors which are near to the boundary surfaces will be associated to the nearer center. This center can not be the correct class center. This result was confirmed through BPN simulation.

2. The BPN training requires comparatively large number of training vectors (we use 1200 corn seeds in our research).

3. Even if there is an enough representative training set, the classification accuracy of the network in the area of boundaries is not high.

4. If the classes from the table 2 are presented by the domain R1 in the space of the objects vectors (*figure 3*) the sittings' domain R2 will surround the domain R1. The centers of R1 and R2 will get into the domain R1 (in this case they will coincide). Regardless of the different positions of the two domains the network will strive to associate the vectors from R1 and R2 to the same center. This is a conflict for every type of network. These problems make the usage of the BP network inefficient.

Another kind of neural network, which can be used for this task is the Kohonen network. On principle, this is a network which clusters the input vectors. Clustering is efficient when the clusters are compact and there is enough distance between them.

Table 2. Names of the classes

X	Y	Z	code
5,5÷7,5	8,5÷9,5	0÷11	1 0 0 0 0 0
3,5÷5,5	8,5÷9,5	0÷11	0 1 0 0 0 0
3,5÷5,5	7,5÷8,5	9÷11	0 0 1 0 0 0
3,5÷5,5	6,5÷7,5	0÷9	0 0 0 1 0 0
3,5÷5,5	7,5÷8,5	9÷11	0 0 0 0 1 0
5,5÷7,5	7,5÷8,5	0÷11	0 0 0 0 0 1

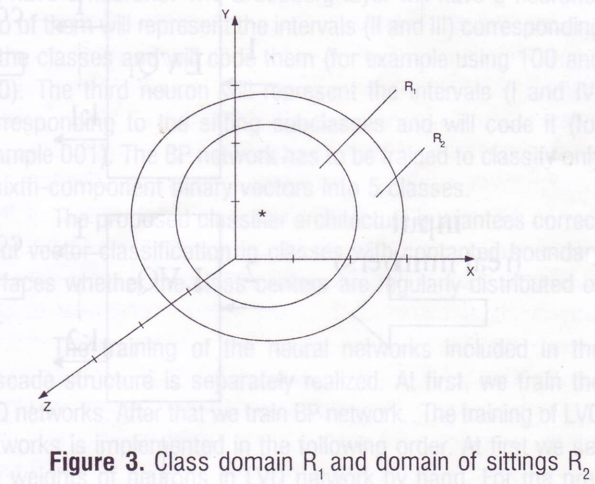

Figure 3. Class domain R_1 and domain of sittings R_2

Whenever there are classes with contacted boundary surfaces the following problems arise:

1. For the correct network work all classes must have the same size in the direction of X, Y and Z. This condition is fulfilled regarding the axis X and Y only.

2. The problem related to the position of the domains R_1 and R2 and their centers exists in this case as well. The Kohonen network finds centers of the clusters and associates input vectors to them. Since this case the centers of the two classes coincide the network will find two new classes which are not corresponing to the real classes.

There is a possible variant for classification using LVQ network — to divide input vectors into 6 classes according to the *table 2* and 54 subclasses presented the sittings. (*figure 4*). The total number of Kohonen nodes is 60. The Grossberg layer can unite all subclasses in one class — sittings.

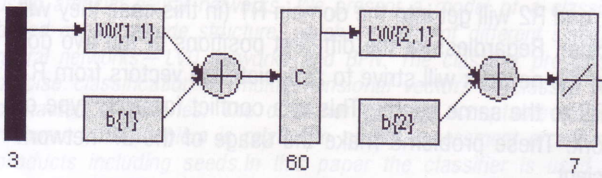

Figure 4. LVQ-network

The problem concerning irregular distribution of the classes exists as well. This is a problem of the Kohonen layer.

This investigation shows that the standard BP and LVQ networks are not appropriate for classifying multidimensional vectors in classes with contacted boundary surfaces when the class centers are not distributed regularly in the space of input vectors. This task requires the development of a new classifier which is presented below.

2.3. Conceptual Model of a New Classifier

The classifier must have the following properties:

— to provide a correct classification of multidimensional vectors in classes with contacted boundary surfaces, whether the dimensions of the classes along the coordinate axis are equal or not;

— to provide a correct classification when the sittings class surrounds the other classes;

— to have an acceptable training recourse.

A conceptual model of a classifier which has the properties mentioned above is shown in *figure 5*.

It has a cascade structure built of two types of neural networks — LVQ and BPN. The classifier includes n LVQ networks (n is the size of the input vectors) and one BP network with N+1 output neurons (N is number of the classes). Each of LVQ networks has one input which is connected to one of the components of input vector and k_i number of outputs where $k_i=m_i+1$ (m_i is the number of the intervals along the axis x_i which corresponds to different classes). For example if the classes define two intervals $\Delta_1 = x_i^1 \div x_i^2$; $\Delta_2 = x_i^2 \div x_i^3$, then k= 3. The idea is illustrated in *figure 7a* (n = 2).

The i-th component (x_i) of the input vector is applied to the input of the i-th LVQ network.

Whenever there are regular intervals along each axis (*figure 6b*), the Kohonen layer contains m_i+2 neurons. Weights of the neurons are equal to the centers of the corresponding intervals ($X_{Icent.}$, $X_{IIcent.}$, $X_{IIIcent.}$, $X_{VIcent.}$). The Grossberg layer encodes the intervals II and III and combines the rest intervals I and VI (sittings) in one and encodes it.

If there are irregular intervals, the Kohonen layer contains $2m_i$+2-n*c neurons (where n is the number of intervals with

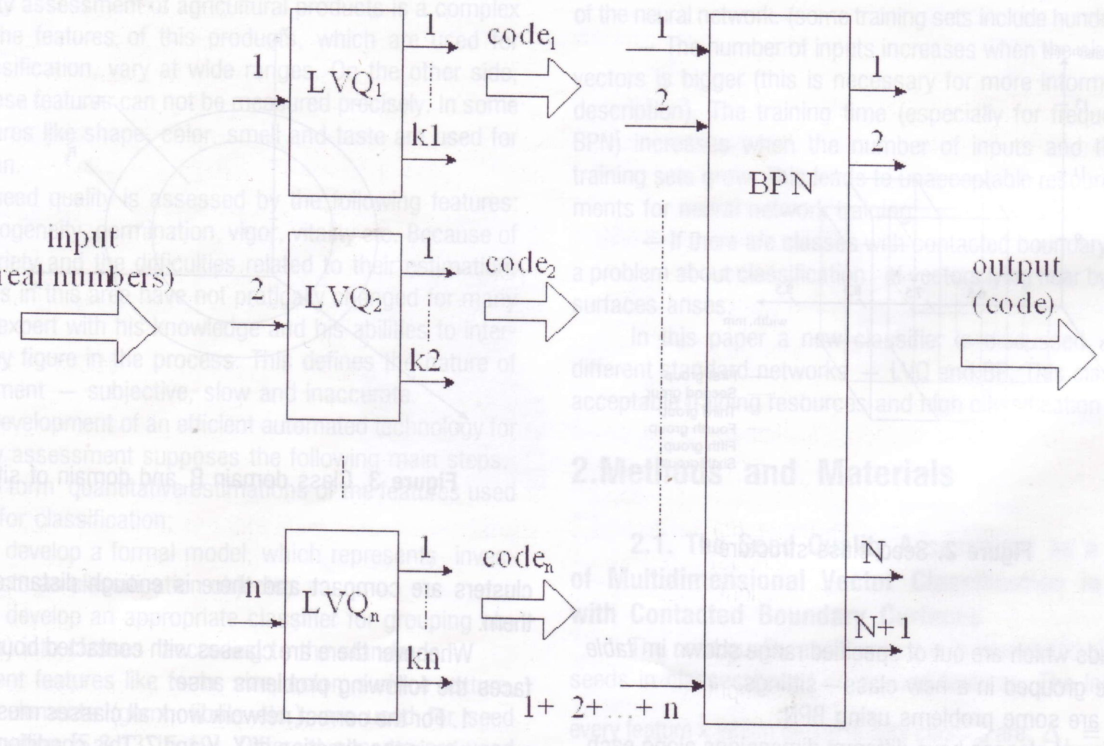

Figure 5. Cascade Neural Network-conceptual model

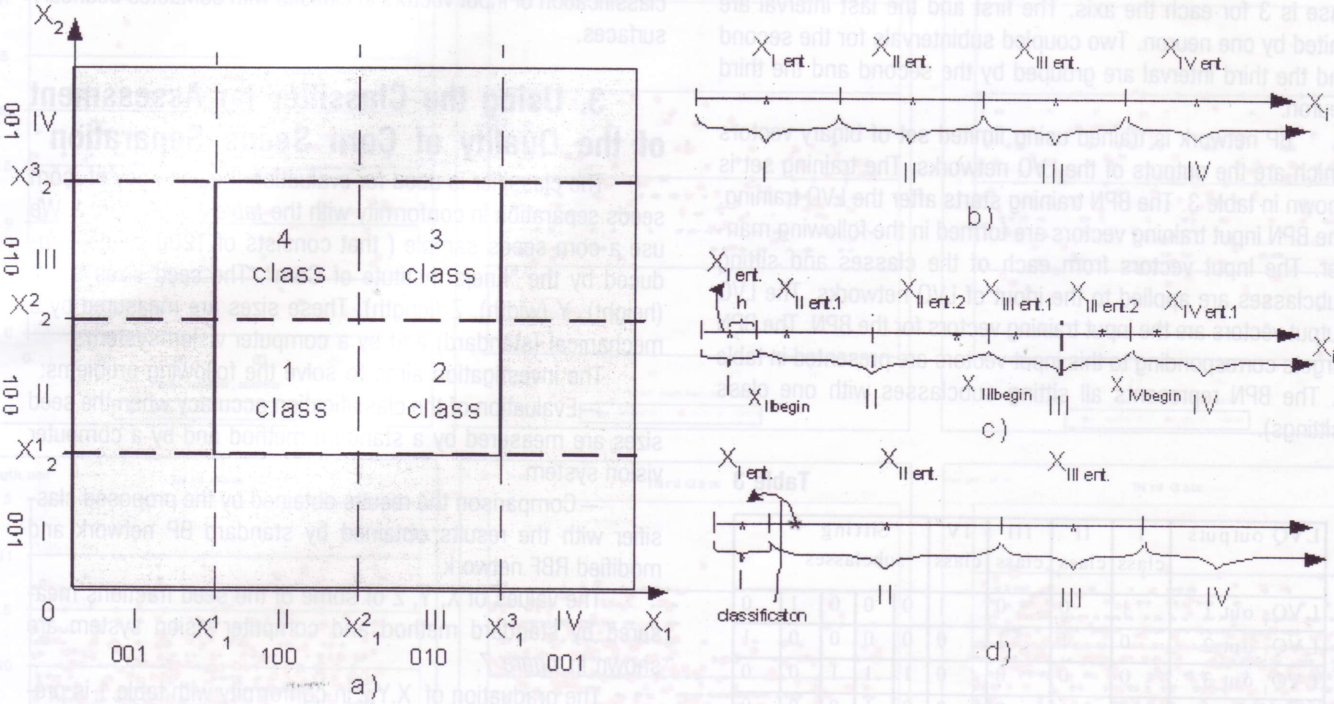

Figure 6. Distribution of the classes and adjustment of Kohonen layer

minimal length; c is a parameter which has value 1 if there is one interval with minimal length and otherwise its value is 0). In *figure 6c* it is shown that all intervals are separated by two subclasses except the smallest and the last interval. The Grossberg layer has m_i+1 neurons. It combines the two subintervals, corresponding to each of the classes. It also combines two intervals (I and IV) which correspond to sitting subclasses and encodes it.

The BP network groups LVQ output vectors in the corresponding classes and codes them. All vectors, which get into the first and fourth interval form a sittings class.

Why do we use different LVQ networks for each component of input vector instead of a standard LVQ network which has n inputs? Letus return to the case presented in fig. 6. If the intervals are regular along each axis (*figure 6a*) the Kohonen layer of the standard LVQ network will consists of 16 neurons. Four of them represent the classes (1,2,3 and 4). The rest 12 neurons represent the sitting subclasses. The Grossberg layer includes 5 neurons – 4 neurons represent classes and the fifth neuron groups all sittings subclasses in one class. This is a typical LVQ network application. If we set the weights precisely (according to the centers of classes and subclasses) the network will correctly classify input vectors. If the intervals are irregular and the weights of Kohonen layer are set according to the centers of classes and subclasses the network will associate the input vectors to the nearer center (*figure 6d*). All vectors which belong to one class (for example to the first class) and are situated nearer to the center of the other neighbor class will be incorrectly classified.

We can avoid this incorrect classification if we use different LVQ networks for each component of input vector. We use two neurons for each interval with the exception of the smallest and the last interval. The weights of these neurons are set in accordance to the values $X_{Icent.}$, $X_{IIcent1.}$, $X_{IIcent2}$, $X_{IIIcent1,}$ $X_{IIIcent2.}$, $X_{IVcent1.}$, presented in fig. 6c. If the input x_i gets into the second interval it will be associated to the $X_{IIcent1.}$ or $X_{IIcent2}$ center (depending on the distance between these two centers). The Grossberg layer unites the outputs of the two neurons in one interval (II). This structure which consists of n LVQ networks guarantees a correct classification of all input vector components. The main role of BP network is to classify the input vector into the correct class. If there are two dimensional input vectors and 4 intervals for each vector component x_i the Kohonen layer will have 6 neurons. The Grossberg layer will have 3 neurons. Two of them will represent the intervals (II and III) corresponding to the classes and will code them (for example using 100 and 010). The third neuron will represent the intervals (I and IV) corresponding to the sitting subclasses and will code it (for example 001). The BP network has to be trained to classify only 9 sixth-component binary vectors into 5 classes.

The proposed classifier architecture guarantees correct input vector classification in classes with contacted boundary surfaces whether the class centers are regularly distributed or not.

The training of the neural networks included in the cascade structure is separately realized. At first, we train the LVQ networks. After that we train BP network. The training of LVQ networks is implemented in the following order. At first we set the weights of neurons in LVQ network by hand. For the presented in fig.6c case the weights in the Kohonen layer are equal to the values $X_{Icent.}$, $X_{IIcent1.}$, $X_{IIcent2}$, $X_{IIIcent1}$, $X_{IIIcent2.}$, $X_{VIcent1}$. The weight of first neuron is set equal to the center of first interval (the smallest interval). The weight of neuron related to the last interval is set to $W_6 = X_{IVbegin}$+h, where h is equal to the half length of the smallest interval. The other intervals are presented with 2 neurons with weights respectively $W_2 = X_{IIbegin}$ +h, $W_3 = X_{IIbegin}$ -h и $W_4 = X_{IIIbegin}$ +h, $W_5 = X_{IVbegin}$ -h.

The number of neurons in the Grossberg layer in this case is 3 for each the axis. The first and the last interval are united by one neuron. Two coupled subintervals for the second and the third interval are grouped by the second and the third neuron.

BP network is trained using limited set of binary vectors which are the outputs of the LVQ networks. The training set is shown in table 3. The BPN training starts after the LVQ training. The BPN input training vectors are formed in the following manner. The Input vectors from each of the classes and sitting subclasses are applied to the input of LVQ networks. The LVQ output vectors are the input training vectors for the BPN. The BPN targets corresponding to this input vectors are presented in table 3. The BPN represents all sitting subclasses with one class (sittings).

Table 3

LVQ outputs	I class	II class	III class	IV class	Sitting subclasses				
LVQ_1 out 1	1	0	0	1	0	0	0	1	0
LVQ_1 out 2	0	1	1	0	0	0	0	0	1
LVQ_1 out 3	0	0	0	0	1	1	1	0	0
LVQ_2 out 1	1	1	0	0	0	1	0	0	0
LVQ_2 out 2	0	0	1	1	1	0	0	0	0
LVQ_2 out 3	0	0	0	0	0	0	1	1	1
BPN Outputs					V class (sittings)				
$Output_1$	1	0	0	0	0	0	0	0	0
$Output_2$	0	1	0	0	0	0	0	0	0
$Output_3$	0	0	1	0	0	0	0	0	0
$Output_4$	0	0	0	1	0	0	0	0	0
$Output_5$	0	0	0	0	1	1	1	1	1

The proposed classifier has the following advantages:

1. A training set of input vectors is not used for LVQ training. The LVQ training is implemented by setting the weights. This simplifies the training procedure and gives a possibility for precise adjustment of classes' centers. That is more accurate in comparison with the case when the classes' centers are obtained by clustering a large number of input vectors. If the classes' centers are obtained by clustering they can be displaced from the real centers of the classes. This will lead to an incorrect classification of the input vectors lying near to the boundary surfaces.

2. BP network is trained by a limited set of binary vectors. For example, if there are two-dimensional input vectors and four classes, the training set contains only 9 six-dimensional binary vectors. The seed separation problem requires a set of 36 ten-dimensional binary vectors. There is not a training error. When we use a standard BPN for seed corn separation there is a training error about 47%.

3. The proposed classifier excludes a priori the possibility for incorrect classification of input vectors in classes with contacted boundary surfaces.

As a conclusion, it could be said that the proposed classifier has an acceptable training resource and gives a precise classification of input vectors in classes with contacted boundary surfaces.

3. Using the Classifier for Assessment of the Quality of Corn Seeds Separation

The classifier is used for evaluation the accuracy of corn seeds separation in conformity with the *table 1* and *figure 2*. We use a corn seeds sample (that consists of 1200 seeds) produced by the "Kneja Institute of Corn". The seed sizes are X (height), Y (width), Z (length). These sizes are measured by a mechanical (standard) and by a computer vision system.

The investigation aims to solve the following problems:

– Evaluation of the classification accuracy when the seed sizes are measured by a standard method and by a computer vision system.

– Comparison the results obtained by the proposed classifier with the results obtained by standard BP network and modified RBF network.

The values of X, Y, Z of some of the seed fractions measured by standard method and computer vision system are shown in *figure 7*.

The graduation of X,Y,Z in conformity with table.1 is presented in fig.8. We simulate our classifier and BPN and RBFN classifiers in MATLAB environment. The architectures of all classifiers are shown in *figure 9*, *figure 10*, *figure 11* and *figure1*.

The results from the simulation show the following:

1. The classification of all seeds from testing sample, measured by a standard method, is correct if we use proposed classifier. There is no classification error. In the same conditions the classification error obtained by the BPN is 47.5%. If the RBFN classifier is used the error is 25.1%.

2. When the sizes of corn seeds are measured by a computer vision system the classification error of proposed classifier, the BPN and RBFN classifiers are respectively 5.8%, 36.1% and 12%.

3. The bigger classification error obtained by the BPN and RBFN classifier when seed sizes are measured using standard method is determined by the fact that big part of input vectors are on the boundary surfaces and near them. When the seed sizes are measured by a computer vision system there is a displacement of the input vectors as a result of measure errors. This leads to better classification of the seeds.

4. Conclusion

1. Standard BP and modified RBF networks do not give a satisfactorily solution of the problem related to the multidimensional vector classification in classes with contacted boundary surfaces. For this task these networks have unacceptable an training resource and a relatively low classification accuracy.

2. The proposed classifier which consists of standard LVQ networks and a BP network can be easily trained. The training of LVQ networks is realized by setting the weights directly. For this purpose we use the coordinates of center of classes and sitting subclasses. The BP network is trained with a relatively small set of binary vectors.

Figure 7. X, Y, Z values measured by standard method and computer vision system

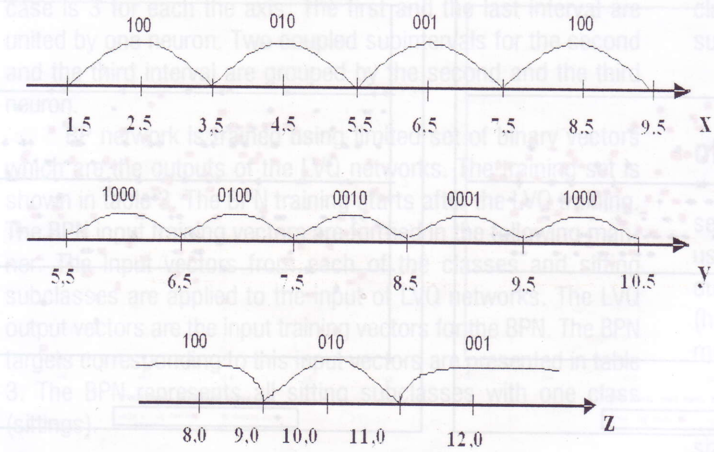

Figure 8. Graduation of the intervals

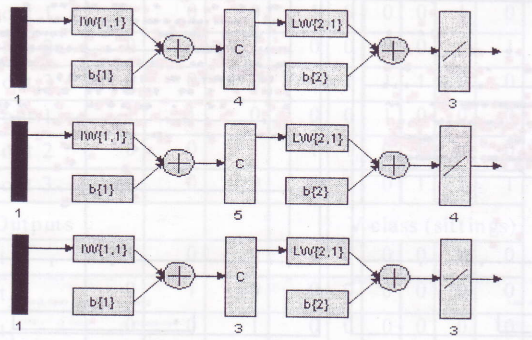

Figure 9. LVQ-networks

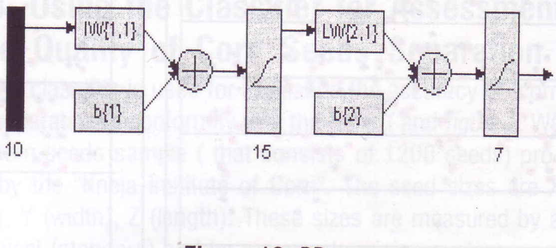

Figure 10. BP network

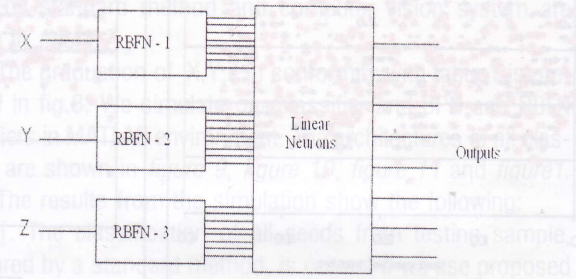

Figure 11. Modified RBFN network

3. The proposed classifier has a bigger classification accuracy in comparison to the classifiers based on a standard BP or RBF networks. The obtained classification errors obtained by the discussed three classifiers are respectively 0%, 47.5% and 25.1% when the seed sizes are measured by a standard method. If the seed sizes are measured by computer vision system the classification errors are respectively 5.8%, 36% and 12%.

4. The classifier could be adapted to different problems related to the seed quality assessment and to the different tasks concerning the multidimensional vector classification in classes with contacted boundary surfaces.

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