Neural Networks Precision in Technical Vision Systems

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Summary
In recent decades, the development of technical vision systems (TVS) has been actively conducted to automate production. To increase the effectiveness of the functioning of TVS, it is necessary to constantly replenish the arsenal of methods and means of preliminary image processing and the construction of classifiers that combine the required indicators for speed and reliability of identification. The main difficulty in developing neural networks (NN) with desired properties is the lack of theoretical design of their topologies and the prediction of recognition accuracy. In this regard, the study of the possible achievable accuracy for the NN recognition of mass objects with strong intra class visual variability and the development of appropriate methods to guarantee a sufficient specified accuracy is an urgent.
Key words:
technical vision systems, neural networks, theoretical design, recognition accuracy, reliability of identification, preliminary image processing, construction of classifier, pattern recognition, system analysis, computer vision.

1. Introduction

The purpose of this research is to develop methods and algorithms for using neural networks in TVS to be recognized, with sufficient accuracy, the mass number of objects of natural origin with strong visual intra-class variability. [5,21]. Subject of research is consider a set of mathematical models and the main architectures of neural networks that allow classification of objects with great visual intra-class variability, implemented programmatically on neuro-imitators. Research used methods of system analysis, pattern recognition, computer vision, neural networks [5,29], mathematical statistics, and spectral analysis.
The practical value of the research is the results of the work were used to develop database software for an expert level laboratory bench for seed production and to create a raw material recognition unit for an expert system for monitoring safety and quality indicators [3,11,28]. The relevance of the research is scientific novelty, theoretical and practical significance which shown and discussed. The purpose and objectives of the research are also given and achieved [30].
Initially, an analytical review of existing approaches to the development of TVS is conducted, which allowed us to draw conclusions that determine the direction of the research. The mathematical methods that make up the algorithm of the formalized approach to the construction of the TVS are determined. The models of informative features that improve the recognition accuracy compared with existing methods are investigated and selected software for simulation of network operation. [19,30].
It is concluded that the methods of object identification for solving a number of urgent problems of selection and seed production, process control, etc. do not have an expert level of recognition accuracy. It is established that the presence of large variability[18,35] of optical properties within one class[6,15] of objects of natural origin is the main problem of identification. As a result of the analysis of existing identification methods, artificial neural networks were selected as one of the most promising approaches for solving a number of problems with objects of the food and grain processing industry[13,31].

2. Research Methods and Framework

In this step of this research it was considered a systematic approach to creating a classifier based on a neural network[9,33]; methods for solving the recognition problem in vision systems; options for making decisions were also considered.
The system analysis process includes a number of stages[12,17,37], the implementation of which is necessary to solve the problem. The combination of these stages in a certain sequence dictated by the structure of the problem and cause-effect relationships leads to a systemic solution. The image recognition algorithm[7,14,25] consists of three components:
1) Transformation of the original image (pre-processing and / or mathematical transformation);
2) Highlighting key characteristics (analysis of the main components, genetic algorithm, etc.);
3) Classification mechanism: statistical methods, discriminatory function method, neural network[2,27], etc. shown in Fig.1.

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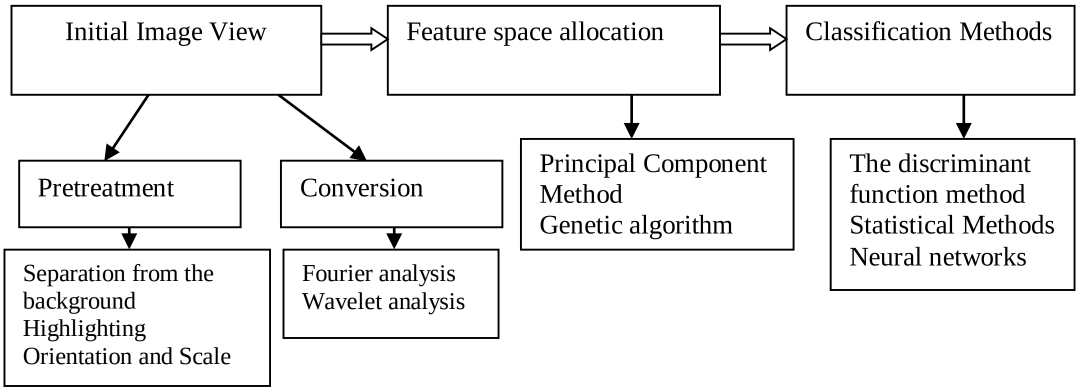

Fig. 1 Structure of the recognition method

Each component of the system must be designed so that for the system as a whole to ensure the achievement of its goals with the required efficiency [3,9,36].

To ensure the invariance of objects with respect to geometric transformations, the image is pre-processed and brought to a standard position, scale and orientation. For the initial image processing, the color histogram method was used to perform threshold binarization of grayscale images[1,10]. The algorithm determines the presence of two classes of pixels in the image - text and background. After the binarization operation[16,22], the search becomes for adjacent areas in the image. Based on the separation of the image into adjacent areas, an array of objects is created, which is an image stored in a separate matrix[20,38,39] (a separate object and its outline).

The contour of a flat image of a component is defined as a discrete set (xi, yi), $1 \le i \le n$, of the Cartesian coordinates of points on a flat closed loop without self-intersections[4,23]. The color of the object is presented in the form of a matrix of pixels (grain in Fig. 2).

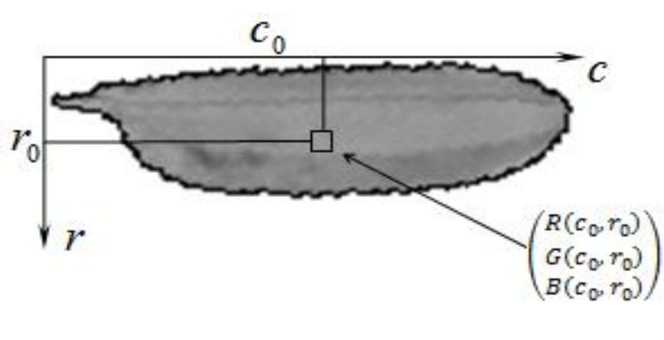

Fig. 2 Representation of grain coloring by a pixel matrix

Each pixel is decomposed into color components in space. $\{R, G, B\}$ - Palettes, R-red, G-green, B-blue. To obtain the characteristics of the color and shape of objects, a discrete wavelet transformation, which is a convolution of the original signal with low-frequency and high-frequency filters, generating a rough approximation and detailing coefficients [8], is more preferable. Obtaining wavelet transform coefficients is most effective using wavelets [26,34]. The resulting spectrum consists of the spectra of the color components R,G and B, taken independently of each other. Computed wavelet spectrum $\vec{Z}$ ={Z0, …, ZN-1} color functions $R(c,r)$, $G(c,r)$ and $B(c,r)$, where c and r - coordinates of the pixel, forms a vector space X of dimension n, which is called a feature space. When the initial attribute space is specified, a smaller number of the most informative features are selected (formation of the attribute space of lower dimension)[3,21]. The main methods used in conjunction with neural networks are the genetic algorithm components (GAC), the principal component analysis and factor analysis. The use of a genetic algorithm to lower the attribute space was time consuming[16,37]. The Statistics in table 1 package implements a non-linear version of the GAC, based on the use of auto-associative networks. In such a network, the number of outputs coincides with the number of inputs, and all neurons have a special property. If the number of elements of the intermediate layer is made less than the number of inputs / outputs[15,29], then this forces the network to compress the information, presenting it in a smaller dimension. The criterion of scree when applying factor analysis allows you to quickly assess the number of main factors[18,30] and leave signs with the greatest dispersion. To achieve the required accuracy, 100 wavelet spectral coefficients were left.

The next part of the research defines the principles of construction and proposes a methodology for creating neural network (NN) for high-precision recognition in TVS[19,23]. A neural network can be represented as some multidimensional function F: X → Y, the argument of which belongs to the attribute space of the inputs, and the value to the output attribute space. Each neuron of the neural network performs the summation of signals from other neurons that have gone through non-linear transformation. Thus, the perceptron approximates the dependencies[33], which in the general case are functions of many arguments; moreover, the perceptron performs this approximation using the sum of functions, each of which is a function of only one argument. The Hecht-Nielsen theorem generalized that any continuous function of n variables f (x1, x2, ... xn) [24,39]can always be represented as the sum of continuous functions of one variable and showed that it can be approximated using a two-layer neural network with direct full connections with n neurons of the input layer, (2n +1) neurons of the hidden layer with previously known limited activation functions and m neurons of the output layer with unknown functions activation.

3. Proposed Methodologies and experimental results

The experimental setup (Fig. 3), developed by a high technologies, includes the following stages of creating a “training” database (DB) for spectral analysis of a flat image and subsequent image recognition:

1) Photo / video shooting of fruits on a plain background; for the "training" database - a known variety, for the operating mode - sort mixes to be recognized;
2) The use of algorithms for separating the background and highlighting pixel images of individual single fruits;
3) The establishment of the center of mass of the object, the angle of rotation relative to the initial coordinate system and the size of each image, the transfer of the origin to the center of mass of the object and the rotation of the coordinate axes so that the abscissa axis runs along the maximum extension of the object;
4) Normalization of the size of the object so that, regardless of the resolution of the analyzed image, the geometric dimensions of all objects coincide;
5) Conducting a discrete wavelet - the conversion of color components of all points (pixels) belonging to the area selected in the previous paragraphs; to order the received coefficients; discard insignificant elements of the resulting ordered array;
6) For the “training” database - save the received data in the database of single wavelet spectra;

7) For neural networks (NN) methods recognizing the DB of single wavelet spectra as a training sample;
8) For the wavelet operating mode, the spectrum of elements of the mixture to be recognized is fed to the input of the developed NN. NN output identifies the elements of the mixture.

Three of the most famous and popular packages were used as a tool for constructing an artificial neural network - STATISTICS Neural Networks 6.1 (SNN), NeuroPro 0.25 and Neural Networks Toolbox (MatLab 7.0.1 expansion pack).

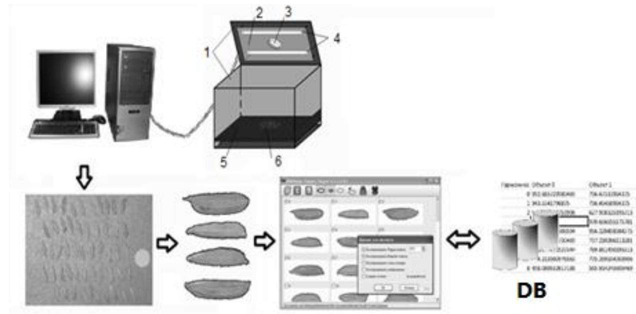

Fig. 3 Diagram of a laboratory setup and the steps for creating a training database: 1 - a container with opaque walls, 2 - frosted glass, 3 - a hole for the camera, 4 - artificial lighting lamps, 5 - a tray for grain, 6 – grains

The objects of research were: elite varieties of unpolished rice, polished and peeled rice, legumes and oilseeds, triticale and wheat (fig. 4). More than 1000 grains gave material for the preparation of a training, testing and control sample. An analysis of the objects of study showed that the L / A (ratio of length to width of rice) in the studied rice varieties varies over a wide range. When comparing the indicators of the level of variation of L / A, significant distinctive features were found. The limits of variation of the L / A indicator significantly exceed the limits of the confidence region, which does not allow for accurate identification of rice.

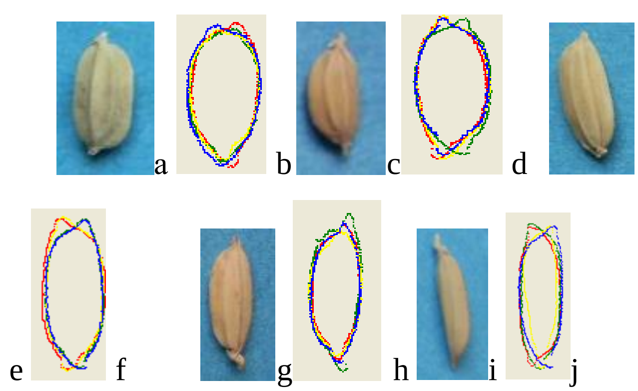

Fig. 4 (a – j) - variability of the contour of the corresponding variety

To create neural networks, an important task is to find the optimal size of the network - such a number of hidden layers and neurons in the layers that will give a minimum of generalization error. Two approaches were used: theoretical and practical, using learning curves - the dependencies of learning errors and generalizations on the size of the neural network. The optimum corresponds to local minima or moments of the graphs reaching asymptotes (Fig. 5b). The experiment was carried out for the task of classifying 5 varieties of unpolished rice. Architecture: a multilayer perceptron with 249 neurons at the input; from 1 to 126 neurons were located in the intermediate layer (Fig. 5a).

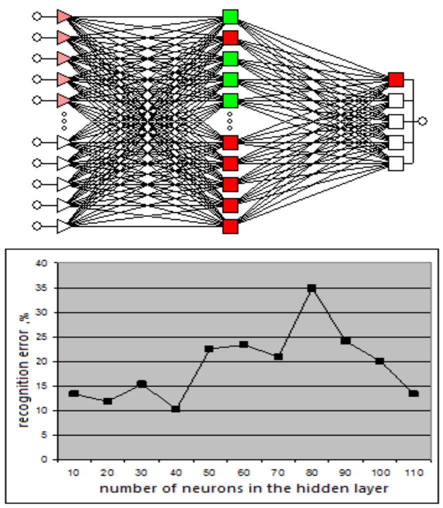

Fig. 5 a network topology, Δ - input layer neurons,

□ - neurons with sigmoid activation functions; b - dependence of recognition error on the number of neurons in the hidden layer

The required number of neurons in the hidden layers of the perceptron is determined by the formula, which is a consequence of the theorems of Hecht-Nielsen:

$$\frac{N_y Q}{1+\log_2(Q)} \le N_w \le N_y\left(\frac{Q}{N_x}+1\right)\left(N_x+N_y+1\right)+N_y \quad (1)$$

Where, N_y is the dimension of the output signal, Q is the number of training examples; N_w is the required number of synaptic connections; N_x is the dimension of the input signal.
Having estimated the required number of synaptic connections N_w using this formula, the required number of neurons in the hidden layers was calculated. The number of neurons in the hidden layer of the bilayer perceptron will be equal to: $N=\frac{N_w}{N_x+N_y}$. Both theoretical calculations and the learning curve determine the optimal size from 40 to 50 neurons in the intermediate layer.

According to the requirement of the Hecht-Nielsen theorem, in the neural networks for both the first (hidden) and the second (output) layers sigmoidal transfer functions with adjustable parameters were used.

4. Results and Practical Implementations

Given a set of training examples and the form of an error function, training a neural network is a multi-extreme non-convex optimization problem. Its purpose is to find the lowest point on a multidimensional surface. Based on a random point on the surface, the learning algorithm gradually looks for a global minimum. For a network like Multilayer Perceptron (MLP), a very good result is shown by the conjugate gradient method and the classical algorithm of back propagation of error. The learning error for the constructed neural network is calculated by comparing the output and target (desired) values. The error function is formed from the obtained differences. The error function is an objective function that requires minimization in the process of controlled training of a neural network. Using the error function, you can evaluate the quality of the neural network during training. To evaluate the classification method obtained, an experiment was conducted to separate 5 varieties of unpolished rice using a neural network (Table 1).

Table 1: Classification matrix for a multilayer perceptron

Class	Share rule (%)	g	i	a	d	b
g	98	266	0	2	1	0
i	100	0	284	0	0	0
a	97	0	0	181	1	1
d	97	2	0	1	132	3
b	97	1	0	1	2	135
Total	98.5	269	284	185	136	139

The network architecture is a two-layer perceptron (Fig. 6), the activation function is sigmoid (logistic), the error function is SOS (equal to the sum (taken from all observations) of the squares of the differences between the target and actual values). To determine the ability of a network of a given configuration to solve the problem, we evaluated the Lipschitz constant of the network (2) and compared it with a sample estimate (3).

$\Lambda_n = \sup_{x,y}\left(\left\|F(x)-F(y)\right\|/\left\|x-y\right\|\right)$, where F is a vector function of the input signals (2)

$\Lambda_t = \max_{i\neq j}\left(\left\|f(x^i)-f(x^j)\right\|/\left\|x^i-x^j\right\|\right)$, where f^i are the values of the function at points x^i (3)

In the case of the network is not able to solve the problem. The Lipschitz sampling constant is equal to 1.79 in our experiment with a norm of the difference of the input signal vectors of 1.57. To reduce the value of the Lipschitz constant, the activation function is replaced by hyperbolic tangent.

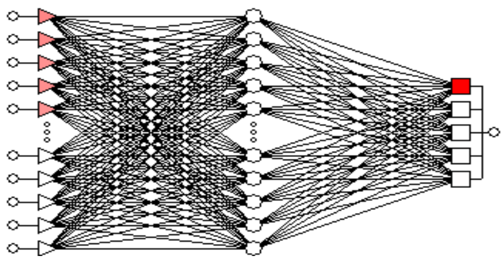

Fig. 6 Network architecture: Δ - neurons of the input layer, □ - neurons with sigmoid activation functions

○ - neurons with the activation function of hyperbolic tangent

The training was conducted using the back propagation method and the conjugate gradient method. The Lipschitz sampling constant is 0.963 with a norm of the difference of vectors of input signals of 2.076. A more difficult classification task is the separation of polished and peeled rice grains of the same variety. At the peeled rice at preliminary cleaning only a husk, a surface layer is removed. Therefore, it has a darker color than polished rice. Of the 115 polished grains, all were correctly classified (100% accuracy), and of the 121 husked grains, 2 were classified as polished (98.35% accuracy).

When processing polished rice, the most difficult to separate weed is broken glass, because in color and translucency, and sometimes in shape, it has a great resemblance to a grain. In 121 polished grains, 20 pieces of broken glass were added, the shape and size of which are closest to the grains. All impurities were isolated with 100% result.

Table 2: Comparison of recognition accuracy for various software implementations for five varieties of unpolished rice

Grades / Method	g	i	a	d	b	Total
Discrimination/ analysis %	89.2	99.3	93.5	92.6	100	94.77
NeuroPro 0.25 %	82.9	100	100	86	80	89.87
Statistica (MLP) %	98.0	100	97	97	97	98.5
MatLab (PNN) %	79.0	97.5	100	100	75	93.5

The next step of the research discusses the practical applications created on the basis of developed methods and algorithms.

For the development of the food industry, it is necessary to introduce expert systems (ES) for monitoring safety and quality indicators in the production process. Inspection of raw materials is one of the stages of the technological process, the quality of the final product depends on the quality of which is carried out in order to remove seeds and fruits unsuitable for processing, as well as impurities and objects. The neural network implementation of the recognition unit of the computing core of the ES is also considered. In the neural network block, the video image of seeds and fruits, subjected to spectral wavelet transform, is the input of a multilayer neural network, the output neuron of which makes a decision on rejection, etc.

One of the stages of the technological process is the separation of oilseeds into varieties. For this separation, varieties (Fig. 7a) were used, which belong to a hybrid variety according to the Network architecture: a multi-layer perceptron with 48 inputs, one intermediate layer and two outputs, activation function neurons - logistic, SOS error function (equal to the sum (taken over all observations) of the squares of the difference between the target and actual values). All 46 grains of the Master variety were correctly classified (100% of the correct classification), and 2 grains of 34 were incorrectly classified as the Master variety (95% of the correct classification). The presence of a recognition error is justified by the high variability of the varieties (Fig. 7b). The separation of refined sunflower grains gives 100% recognition.

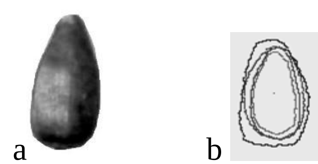

Fig. 7 a grain varieties; b - variability of the contour of sunflower varieties

The object of the study was maize varieties (Fig. 8), which are used in the canning industry. The network architecture is a multilayer perceptron with 54 input neurons, an intermediate layer of 34 neurons and one neuron at the output (Fig. 9). The activation function of neurons is logistic, the error function is SOS (equal to the sum (taken over all observations) of the squares of the differences between the target and actual values). The benchmark productivity is 1, the test productivity is 0.928, and the learning error is 0.000110. For a neural classification network, a measure of productivity indicates the proportion of correctly classified observations.

Learning is a backpropagation algorithm for 100 epochs and a method of conjugate gradients with network restoration with the least control error. Of the 42 grains unsuitable for canning, only one grain was mistakenly declared fit (97.62% of the correct classification). Since the rejection was due to external damage, this percentage of error is acceptable for the canning industry.

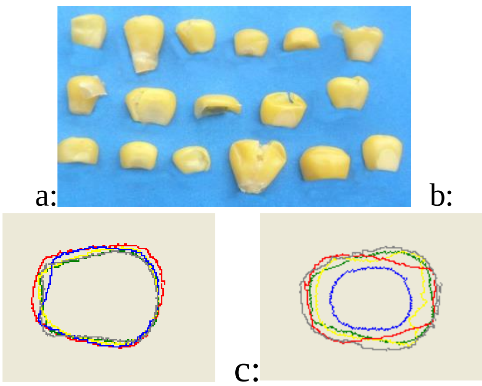

Fig. 8 a Original images of corn, b – variability contours of suitable grains, c- rejected grains

The third object of study was canned green peas (Fig. 9). The network architecture is a multilayer perceptron with 250 neurons at the input, two intermediate layers of 127 neurons and one at the output. The activation function of neurons is logistic, the error function is SOS (equal to the sum (taken over all observations) of the squares of the differences between the target and actual values). The benchmark performance is 0.937, the test is 0.9937, and the learning error is 0.00199. Learning Algorithms: The first stage is the backpropagation algorithm in 100 eras; the second stage is the conjugate gradient method. For both stages, damped regularization of the scales with a parameter of 0.01 was used. Out of 22 peas with external damage, only one grain was recognized as suitable for conservation (95.45% of the correct classification).

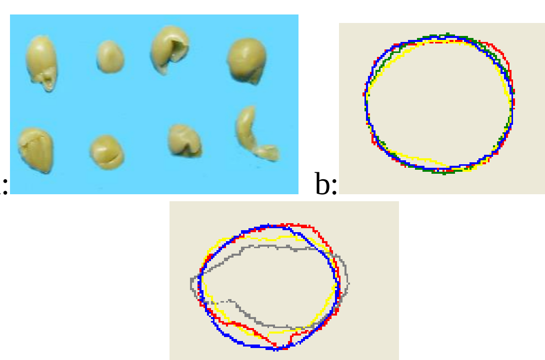

Fig. 9 a The source image of the rejected pea grains, b - variability of the contours of suitable grains,c - rejected grains

Thus, the use of the standard neural network topology — a multilayer perceptron, without changing the activation function and error function, using gradient teaching methods of the first and second order allowed us to conduct a fairly high-quality assessment of the quality of input products for different types of vegetable and oilseeds.

5. Results and Conclusions

As a result of a systematic study, it was shown that to solve a number of urgent problems of breeding and seed production, process control, etc., the necessary increase in the efficiency of TVS functioning to an expert level of accuracy, for recognition of mass objects of natural origin with strong intra-class variability, is achieved by the method of neural networks. Also the choice of the attribute space based on the wavelet transforms for recognizing objects with great visual intra-class variability is justified. In addition, a training database has been compiled from wavelet spectra of color functions for a software package for neural network recognition of objects of natural origin with strong visual variability of intra-class properties. The research leads to an approach to constructing a neural network based on a multilayer perceptron, which allows recognition of the maximum level of accuracy, is proposed, the appropriate learning algorithm is selected.

Experiments were conducted to verify the operability and effectiveness of the developed neural network at various objects of natural origin. The use of a neural network classification mechanism allows us to carry out 98.5% of the correct separation by grades of cereals, oilseeds and legumes, as well as to produce 100% separation of impurities from the mixture. The system for recognizing varieties and isolating impurities of the neural network block of an expert quality control system in the production of canned food from vegetable raw materials is implemented in software implementations.

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