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WAVELET NEURAL NETWORK FOR NON-DESTRUCTIVE EGG FRESHNESS DETERMINATION

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Wavelet neural networks are a subclass of neural networks which combine wavelet transform methods. The present research tries to enhance the efficiency of classifiers in automated quality determination and sorting systems based on images that have been obtained via spectroscopy in the visual and near-infrared regions (*VIS-NIR*) of the electromagnetic spectrum. The problem at hand has to do with non-destructive egg freshness determination through a transmitted light flow, which is one of the major indicators of egg quality. The research has the following aspects: synthesis and training of wavelet neural networks for different wavelet functions and nondestructive egg freshness determination problems. Three types of wavelet neural networks have been studied, with Morlet, Gaussian and Mexican Hat wavelets as transfer functions in the wavelet neural layer.

Keywords: Artificial neural network, Wavelet basis, Nondestructive quality evaluation**,** Egg freshness.

Introduction

Recent years have witnessed a growing application of the technologies for information processing based on the combination of methods belonging to different spheres of science and engineering. There is a proliferation of works which prove experimentally that neural network theory can be successfully combined with methods stemming from wavelet transform theory, genetic programming, fuzzy logic, etc [11, 12].

The theory of wavelet transforms has been applied successfully in various areas of signal processing. One of the prerequisites for that is the accurately formulated and informative mathematical approach to the realization of the so-called multiresolution analysis which has great many applications. Specialized literature has been focusing more and more on new techniques combining wavelet transforms with a variety of methods for soft computing. Such a technique is exemplified by wavelet neural networks. In general, the mutual usage approaches are classified into two categories. In the first case, the wavelet transform does not participate directly in the training process [2,3]. The signal is first decomposed and then the decomposition coefficients are used in the training of a conventional neural network. In image recognition applications, this process is associated with the formation of a feature space. The main advantage of this approach is the decomposition into a time-frequency scale and the analysis of the signal in various bases. When using the adaptation properties of neural networks with reference to the feature vector, it is possible to eliminate the process of selecting a set of features. Thus, the combination of a wavelet transform and neural networks represents a helpful tool in the synthesis of features by reducing the heuristic approach to a minimum in the formation of a feature space as well as by the elimination of complicated procedures for seeking the most informative set of features. It has been shown [4] that neural networks have limitations with respect to the characterization of local features, such as discontinuities in curvature, jumps in value or other edges. More specifically, such features can be observed in the search for descriptors for the qualitative analysis of eggs [10]. These local features, which are located in time and/or frequency, give significant discriminant information about pattern classes while wavelet transforms allow for the application of this information.

The second case has to do with the morphological and procedural integration of the two methods in so-called wavelet neural networks (*WNN*).

Wavelet neural networks can be compared to a type of the most commonly used neural networks – radial basis function networks – including *SVM*-networks with Gaussian kernel functions. The major advantages of this approach are the following:

Non-linear transformation of the multidimensional input signal into a scalar quantity by means of a basis function. This results in certain invariance of the dimensionality of the network to the dimensionality of the input vector. Hence, the formation of networks with less neurons and adjustment parameters to approximate complex non-linear functions.

Training allowing for the acquisition of local properties, or a balance between local and global approximation possibilities, by means of localized basis functions. This characterizes the degree to which the network, in the training cycle, keeps its input-output function (its adaptation), obtained for a given initial part of the training sample, with subsequent objects which are not in the surroundings of the previous objects.

Materials and methods

VIS-NIR spectroscopy measurement for egg freshness prediction

Egg freshness determination is an important task in view of today's requirements for food safety. Eggs are a widely consumed food product whose quality largely depends on weather and storage conditions. In order to preserve the quality and safety of eggs and egg-containing products, it is necessary to develop rapid and reliable methods for their determination.

Egg quality is a term combining certain parameters having to do with the internal and external state of eggs. External egg quality is related to the egg shell, its state, structure, shape, etc., whereas internal egg quality depends on the purity and viscosity of the albumen and the egg yolk, the size of the air cell, the shape and colouring, etc.

The market and manufacturing criteria for egg quality boil down to requirements concerning freshness, the presence of interior and exterior defects, the weight, density and shape (egg index, asymmetry) of eggs, the ratio between the weight of the albumen and that of the egg yolk, and the size of the germinal disc. A relatively new piece of research [9] manifests the possibility to use shell colour for monitoring the stress and health status of a layer flock.

The changes taking place in eggs during storage are complex and bear upon the functional properties of the egg yolk and the albumen. These changes include: thinning of the egg white, an increase in the pH, weakening and stretching of the vitelline membrane and an increase in the egg yolk moisture content. To a certain extent, egg freshness is explainable in terms of the alteration of some biochemical, microbial, and physical parameters, so it may be defined as their characteristic and objective property. The properties typical of eggs immediately after hatching are to be known as well as the changes in these properties in time. This information can be obtained when conducting controlled experiments during egg storage with the help of measurements concerning the dynamics and the rate of the changes taking place. For this purpose, it is preferable to combine a number of measurements obtained from different methodologies and to compare their results to the expert evaluations.

The most commonly used method for egg freshness determination was proposed by R.Haugh in 1937 and is considered to be the most indicative one of egg quality. According to this method, the egg is weighed first, then it is broken on a flat surface and a micrometer is used to determine the height of the firm egg white surrounding the yolk. The *Haugh*-units which define egg freshness are calculated analytically on the basis of the following:

$$\mathrm{HU} = 100\log_{10}\left(\mathrm{h} - 1.7\mathrm{w}^{0.37} + 7.6\right)$$

where h is the height of the egg white in mm and w is the weight of the egg in gr. The last decade has seen a growing interest in the research on spectral methods and, in particular, on the visible and near-infrared spectroscopy for non-destructive egg freshness determination [4,6] as well as in the application of these methods to automated control systems. In this case, the determination of HU for egg freshness or the visual ovoscopy establishing other characteristics are used as reference methods in the building of models.

The experimentally obtained spectral egg characteristics are a source of information concerning the physical, biochemical, and physiological state of the objects undergoing evaluation, thus contributing to the search for efficient approaches to objective determination of egg quality with sufficient for practical reasons accuracy.

In the present research, the authors established the spectral transmittance characteristics in the visible and part of the near-infrared region (550-850nm) of 60 eggs for a 32-day period.

The formation of a sample begins with the determination of the spectral characteristics on the second day after hatching, followed by a regular examination of the characteristics after a given period of time. To get reliable results, the research team obeyed all storage requirements specified by the BDS 358-80 Bulgarian state standard. The spectrograms obtained can be subjectively divided into a number of classes, for example, three: the first class corresponds to the state of the eggs until Day 4 after hatching, the second class – to the state of the eggs between Day 5 and Day 10, and the third class – to the Day 11 – Day 35 period. A double-beam Cary 100 (VARIAN) spectrophotometer is used, certified in accordance with the ISO 9001 quality control system.

Under these conditions, the problem is reduced to the synthesis of a classifier satisfying all the necessary accuracy requirements.

Wavelet neural networks

Wavelet neural networks (WNN) were described for the first time by Zhang and Benveniste [13] as a new, universal method for the approximation of complex functions with a great rate of convergence. The basic property of wavelets is represented by the possibility for time-frequency decomposition with resolution having dual properties in both regions. The set of continuous wavelet functions is defined by an initial, basis wavelet $\psi(x)$ and variable parameters - d, determining the width (dilation) and t (translation) determining the location in the temporal (spatial) series. Thus, the wavelet $\psi_{d,t}$ is defined as follows:

$$\psi_{d,t} = \psi((x-t)/d)$$

The basis wavelet can be regarded as a bandpass filter whose scaling parameter determines the pass band. The use of the thus formed set of wavelet functions and their localization (Fig.1) allow for a decomposition of the signal into different frequency bands (multiresolution analysis). Fig.2 shows the so-called scalogram, which is the commonest means of presenting results, illustrating the frequency-time characteristics of the signal. Time is plotted on the abscissa, frequency – on the ordinate, in a $\log(1/d)$ scale, whereas the absolute value (decomposition coefficients) is plotted on the applicate.

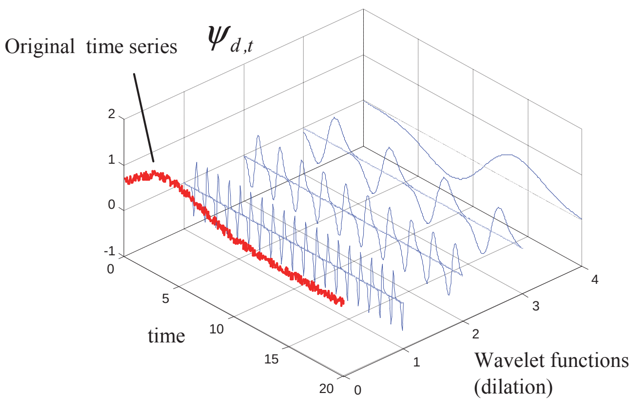


Figure 1. Wavelet wave packets formed with *a Gaussian function* ($\psi_{d,t} = -xe^{-x^2/2}$).

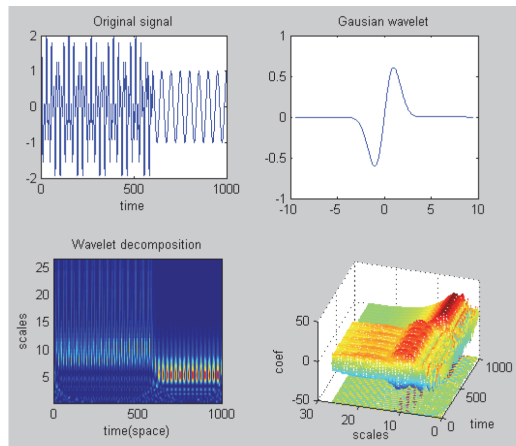


Figure 2. Scalograms for continuous *wavelet transform.*

Wavelet neural networks are networks in which the activation functions are scaled and translated wavelets $\psi_{d,t}$: $\Re^n \to \Re$ (n – dimensionality of the input vector). The generalized representation of a wavelet neural network consists of three layers (see Fig. 3).

The feature vector with an n dimensionality, $X = \{x_1, x_2, ..., x_n\}$, is fed into the input layer of the neural network. At the output of the hidden layer with wavelet activation functions, the $\varphi_1, \varphi_2, ..., \varphi_{n_{hid}}$ outputs are obtained, each of which being defined as:

$$\varphi_j = \psi_{d_j,t_j}\left((\sum_{i=1}^{n_{in}}((w'_{ij}x_i + b'_j) - t_j)/d_j) \right),$$

$$j = 1,2,...,n_{hid}, i = 1,2,...,n_{in}, \quad (1)$$

where: i is the index of the corresponding input; j is the index of a neuron from the second layer; $w'_{ij} \in W'$ is the weight of the link at the i input to the j neuron; $b'_j \in B_1$ - bias; $d_j \in \mathbf{d}$, $t_j \in \mathbf{t}$ are wavelet parameters.

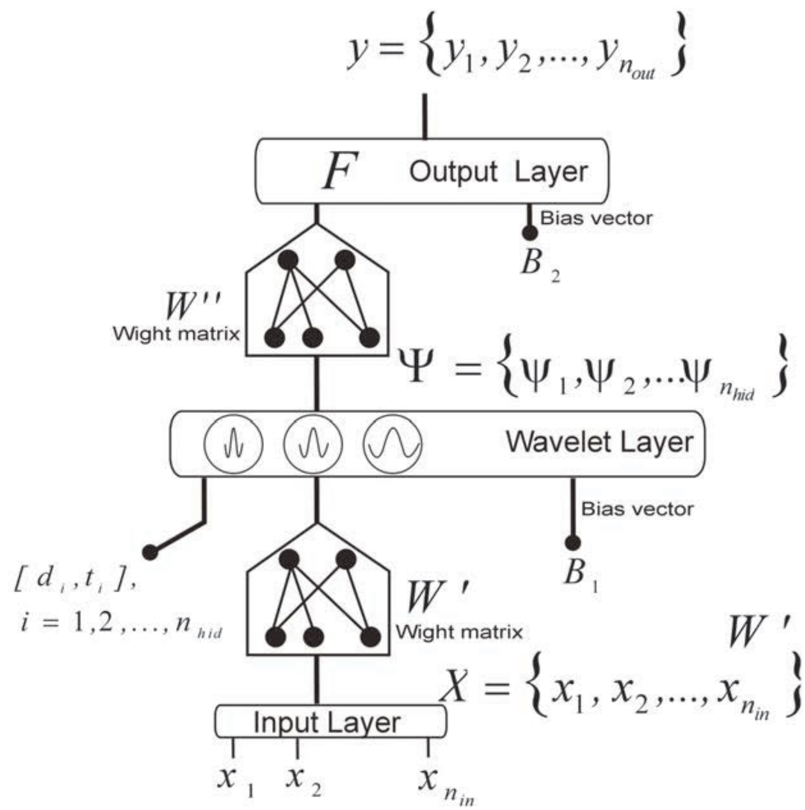


Figure 3.. A wavelet neural network structure.

The output layer consists of neurons determining the network outputs in accordance with the functions:

$$y_k = f_k(\sum_{j=1}^{n_{hid}} w''_{jk}\varphi_j + b''_k), \quad k = 1,2,...,n_{out} . \tag{2}$$

The $f_k \in F$ function is an activation function for the output layer. What is used is usually a linear function or a conventional one, e.g.: a sigmoid function, a tan-sigmoid function, etc.
In network training, there is minimization of the mean-square error between the desired and the real network output:

$$E(\theta) = \frac{1}{2}\sum_{k=1}^{n_{out}}(\hat{y}_k - y_k)^2 \tag{3}$$

where $\hat{y}_k$ is the k-th desired network output. The optimization parameters form the set $\theta = \{W', W'', \mathbf{d}, \mathbf{t}, B_1, B_2\}$. The analogy with the discrete wavelet transform is made when using wavelets defined in advance through the set:

$$\{\alpha^{t/2}\varphi(\alpha^t x - p\beta)\},$$

where α and β are preset constants while t and p are integers (specified in the so-called dyadic grid). These networks are known as wave networks and are characterized by training methods differing from gradient ones.

The conventional approach to WNN training resorts to the back propagation algorithm on the basis of a criterion for the minimization of the mean-square error. The known possibilities are used with a momentum for reducing the sensitivity to local minimums and adaptive training frequency in order to cut down the training time. In general, the adjustment of the parameters is $\theta^{ep} = \theta^{ep-1} - l\Delta\theta$, where $l \in [0.1, 0.9]$ is the learning rate.

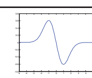
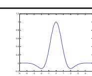
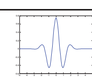
The training of WNN also makes use of genetic optimization algorithms, particle swarm optimization [8], stochastic gradient algorithms and so on.

Results and Discussion

Used Wavelets

In application of wavelet analysis, a wavelet function is usually selected by empirical or trial-and-error methods, according to the characteristics of the analyzed signal and the background of application. The theory of wavelet transforms offers a few classic basis functions which can have various applications. The current research is focused on the wavelet functions shown in Table 1 which are characterized with their indisputable selection properties as well as with a good time-frequency localization.

Table 1.

Gaussian wavelet: $\varphi(x) = -xe^{-\frac{x^2}{2}}$	
Mexican hat: $\varphi(x) = (1-x^2)e^{-\frac{x^2}{2}}$	
Morlet: $\varphi(x) = \cos(\lambda x)e^{-\frac{x^2}{2}}$	

Network parameters

One of the major issues in network training is the determination of the number of neurons on the wavelet layer. In turn, they determine the number of scaling and localizing parameters in the wavelet basis. A possible means of optimization [1] is based on the so-called incremental construction algorithms having to do with a consecutive increase in neurons. The algorithm includes:

1. Presetting an initial minimal number of neurons $m \in \{0,1...,M\}$ at an iteration of $i = 1$.
2. Training the neural network until achieving zero values of the gradient of the wavelet coefficients parameters $\Delta_{i,d,t} < \varepsilon_1$.
3. Evaluation of the mean-square error and comparison with a preset minimal acceptable value.
4. When the condition is not met, there is a transition to Step 1) with an increase in the neurons in the hidden layer to $i = M$.

Obtained results

The sample available consists of 819 images and is subdivided into classes, as shown in Table 2:

Table 2.

Class1	*Class2*	*Class3*	*Total number of pattern vectors*
Eggs until Day 4 after hatching	Egg 5–10 days after hatching	Egg 11–35 days after hatching	
118	*177*	*524*	*819*

Class 1 corresponds to the training set of fresh eggs with the characteristics being registered until Day 4. *Class 2* represents eggs stored for 10 days under normal conditions and *Class 3* includes the egg patterns after this period.

The dimensionality of the vectors is reduced to 25 frequencies with a uniform distribution in the range of 550 – 850nm. Fig. 4 manifests the realizations that have been randomly selected by the training sample.

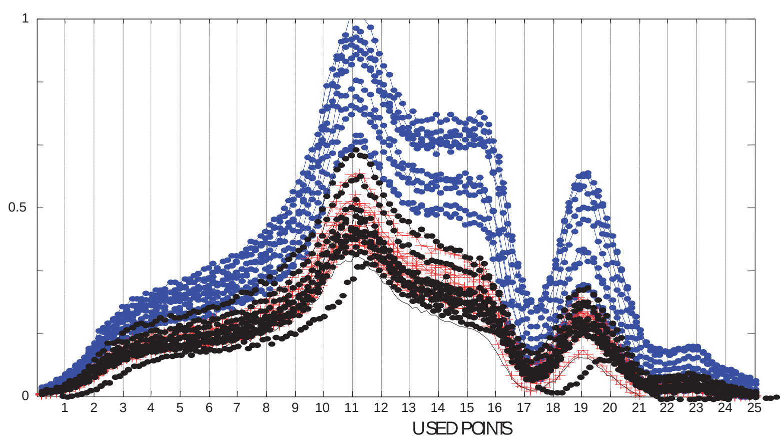


Figure 4. Spectral images of eggs belonging to three defined classes.

For training purposes, 60% of the overall sample are used and 40% for testing. Prior to each procedure, random permutation and division into the two samples are carried out. Fig. 5 shows a typical trend of learning, with minimization of the mean-square error. The learning manifests a fast convergence of the algorithm in comparison with traditional neural networks. A disadvantage is that the results are largely sensitive to the parameters of learning rate and momentum which are selected heuristically. This disadvantage is caused by the usage of the same values in the actualization of the network parameters $\theta = \{W', W'', \mathbf{d}, \mathbf{t}, B_1, B_2\}$, which are initialized randomly in the beginning although they may have values with different dimensionalities.

Table 3 demonstrates the results from the mean-square error for the wavelets under consideration, minimized on the basis of neural network architecture (the number of neurons on the hidden layer is incremented with three neurons per step).

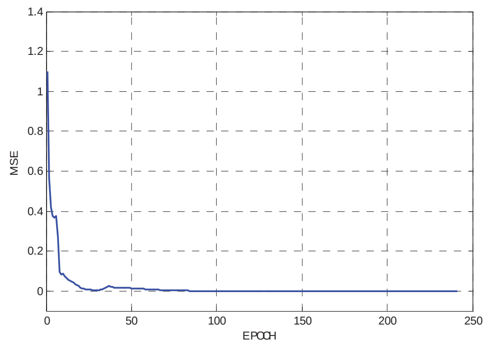


Table 3.

Wavelet	MSE	$n_{in} - n_{hid} - n_{out}$
Gaussian:	$6{,}38.10^{-3}$	25-24-3
Mexican hat:	$12{,}60.10^{-3}$	25-30-3
Morlet: $\lambda = 0.4$	$7{,}45.10^{-3}$	25-27-3

Figure 5. Wavelet network learning for *a Gaussian wavelet.*

To analyze the results, the probabilities for error in the classification are determined, as shown in Table 4 for a Gaussian function.

Table 4.

Gaussian wavelet									
Train error			6.4%		Test error			10.03%	
Confusion matrix (train)					Confusion matrix (test)				
		Predicted Class					Predicted Class		
	class	1	2	3		class	1	2	3
Actual Class	1	**<u>61</u>**	6	0	Actual Class	1	**<u>42</u>**	9	0
	2	4	**<u>83</u>**	15		2	5	**<u>56</u>**	14
	3	0	7	**<u>324</u>**		3	0	4	**<u>189</u>**
		Class1	Class2	Class3			Class1	Class2	Class3
Errors of Commission, %		6.1	13.5	4.4	Errors of Commission, %		10.6	18.8	6.8
Errors of Omission, %		8.9	18.6	2.1	Errors of Omission, %		17.6	25.3	2.0

The best results were obtained via the usage of a wavelet neural network with a Gaussian wavelet. The results for the error matrices (Table 4) lead to the conclusion that the basic difficulty lies in the objects between Class 1 and Class 2 as well as those between Class 2 and Class 3. This is because the sample is divided into time periods which follow one after the other and the boundary scanning results in training images with analogical characteristics in a different class. The advantage in this case is the lack of a minimum error of the classifier (2% for Class 2 and 0% for Class 1) for Class 3 objects (non-fresh eggs).

Conclusion

The training sample thus formed and the training of a classifier indicate the possibility to use spectrometric information in non-destructive determination of egg freshness. For the purposes of classification into three classes, a wavelet network was used. Satisfactory error levels were obtained and basically the probability for misclassifying non-fresh eggs as fresh. With the intermediate class (Class 2), the error probability is greater. In such cases, a batch may be tested additionally or the values of the output layer of the neural network may be used if they are regarded to be probabilistic. The future research on the issue will necessitate evaluation of the reliability of the method in a system for egg freshness monitoring under work conditions as well as the combination of additional sensory information via data fusion. For instance, such opportunities are provided by electronic nose based systems or low-resolution proton nuclear magnetic resonance spectroscopy [6,3].

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