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Complex assessment of food products quality using analysis of visual images, spectrophotometric and hyperspectral characteristics

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***Abstract—* This paper presents a new approach and a platform for complex, nondestructive, express evaluation of quality and safety of food products based on analysis of visual images, spectrophotometric characteristics and hyperspectral images, followed by fusion the results of these analyzes with the aim of categorization of the investigated products in quality groups. Within the context of the problem, the complex evaluation includes an assessment of the appearance and visual characteristics of the investigated product, evaluation of properties associated with the composition of the product and the distribution of the properties on its surface. The focus is on the assessment of the main indicators of quality and safe storage of basic foodstuffs, such as meat, structural bacon, white brined cheese and yellow cheese from cow's milk. The problem of the complex evaluation of the investigated products is represented by the following main tasks: 1) The formal description of the investigated objects by fusion the data from color images, spectral and hyperspectral characteristics; 2) Extraction of specific features of the investigated products; 3) Evaluation of data separability in the following two aspects: separability of individual areas (e.g. areas with meat, fat and bone tissues) on a certain day of product storage and separability of data for the same area on different days of storage and 4) Classification of the objects in quality groups.**

Index Terms— **food products, quality and safety assessment, image, spectra and hyperspectral analyses**

I. INTRODUCTION

Food quality and safety is an issue that is been engaged a number of famous people and scientists from ancient times till now. And this is not accidental. According to the World Health Organization one of the key measures of the quality of life is the quality of the food. There are scientific hypotheses that rational nutrition can prolong life up to 120-150 years. Food is the foundation of all important processes in the human body. The name of the famous Chinese philosopher Confucius is connected with the ancient Chinese proverb "*Whoever is the father of an illness, his mother is poor nutrition*".

The traditional methods for assessing the Quality and Safety (QS) for food products are: sensory evaluation, chemical and microbiological analysis. These are laboratory methods that require specific conditions, equipment, materials and personnel with relevant training. They are not suitable for "on-line" monitoring, suggesting the existence of substandard or unsafe foods in the production and storage. Furthermore, they do not allow correction of the process in order to correct the resulting imbalance in "real time". They are not suitable for express evaluation of food QS "on the ground" - in stores, warehouses, catering, home, etc., where they are not always stored at regulated by the manufacturer conditions.

As an alternative to traditional methods, methods for express non-destructive evaluation of food QS are more and more widely applied in recent years. Among them the most perspective are noncontact optical methods based on analysis of color images, spectrophotometric and hyperspectral analysis.

The purpose of this study is to present a new approach for complex, non-destructive, express evaluation of quality and safety of food products (meat, structural bacon, white brined cheese and yellow cheese from cow's milk) based on analysis of visual images, spectrophotometric characteristics and hyperspectral images, followed by fusion the results of these analyses with the aim of categorization of the investigated products in quality groups.

The problem of the complex evaluation of the investigated products is represented by two main tasks: 1) The formal description of the investigated objects by fusion the data from color images, spectral and hyperspectral characteristics; 2) Extraction of specific features of the investigated products; 3) Evaluation of data separability in the following two aspects: separability of individual areas (e.g. areas with meat, fat and bone tissues) on a certain day of product storage and separability of data for the same area on different days of storage and 4) Classification of the objects in quality groups.

II. OBJECTS OF STUDY AND CHARACTERISTICS EVALUATED.

Main objects of the study are widespread food products such as meat, structural bacon, white brined cheese and yellow cheese from cow's milk, in storage conditions different

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from those covered by the manufacturer (at 20ºC and a lack of illumination).

The main characteristics of the investigated objects and the methods of their evaluation are presented in Table 1.

TABLE 1. THE MAIN INVESTIGATED CHARACTERISTICS AND THEIR CHANGE DURING STORAGE

Object	Type of changes	Method for evaluation
White brined cheese and yellow cheese	Surface color characteristics and their changes during storage.	Organoleptic assessment. Analysis of color images. Spectrophotometry.
	Appearance of colonies of mold, fungi and yeasts and their changes during storage.	Microbiological analysis. Visual image assessment. Analysis of spectral and hyperspectral characteristics.
	Acid degree ° T. Changes in acid degree.	Chemical analysis. Visual image assessment. Analysis of spectral and hyperspectral characteristics.
Pork meat and structural bacon	Surface color characteristics and their changes during storage.	Organoleptic assessment. Analysis of color images. Spectrophotometry.
	Water content. Changes in water content during storage.	Chemical analysis. Visual image assessment. Analysis of spectral and hyperspectral characteristics.
	Acid degree ° T. Changes in acid degree.	Chemical analysis. Visual image assessment. Analysis of spectral and hyperspectral characteristics.

The great variety of quality indicators of food, even considered a narrower aspect, concern fundamentally different properties associated with visual perception (appearance, shape, color, surface texture), with physical, chemical, biochemical and biological characteristics. It is natural to expect that not all of the key indicators of quality can be assessed using a single approach based on information from a particular source, which forms indirect data about food quality. As part of indicators is evaluated by experts based on its visual perception, this was the reason for researchers for assessment of these indicators to use image analysis by computer vision systems (CVS) [3]. For another group of indicators, which are related to the internal structure and composition of food, it is not possible to be measured by image analysis. For evaluation of such indicators computer analysis of the spectral characteristics of the product, formed by a suitable spectrophotometer, as well as analysis of data formed by hyperspectral camera can be applied.

III. STATE-OF-THE-ART. COMPUTER VISION, SPECTRAL AND HYPERSPECTRAL ANALYSIS AS AN ALTERNATIVE TO THE TRADITIONAL METHODS

A. Evaluation of food quality indicators using color image analysis.

In the dairy products industry Computer Vision Systems (CVS) are mainly utilized for evaluation of: color characteristics and texture features of cheese and cheese melting [4], degreasing control [11], to determine the distribution and the amount of spices, vegetables and other components [9], for predicting the moisture content and evaluation of fat content of the cheese [11], for detecting microorganisms [15] and other features of cheeses and dairy products [25].

Computer vision is a fast growing and useful alternative to expert assessment of meat and meat products [5]. By CVS and statistical modelling key attributes of fresh meat and processed meat products, related to their QS, can be extracted and evaluated. This approach has proved its relevance in a series of assessments of the characteristics of the products in the visible and infrared region of the spectrum [13]. Basic features of meat and meat products that may be determined by image analysis are: appearance of pork and veal [8], color characteristics of the meat tissue and areas of fat in fresh meat [13], the fat content of pork and veal pieces [2], defects in fresh meat and detection of microorganisms in the composition of the meat [26], determining the contents of the pieces of muscle tissue forming the ham [14], determining the texture of the surface [21].

B. Evaluation of food quality indicators using spectral analysis systems

The near infrared spectroscopy (NIRS) is a non-destructive technology, which is mainly used for determining the composition of a variety of dairy products such as milk [23] and cheese [8] as well as evaluation of major QS indicators of these products. Some typical examples of the application of NIRS analysis for assessment of various features associated with QS of dairy products may be indicated: determining the sensory features and age of cheese [8]; determining the composition of cheese [20]; the composition of cow's milk [23]; of moisture, fat, and inorganic salts in the processed cheese, analysis and prediction of maturity and sensory features of the cheddar cheese [8], etc.

Main features of the meat and meat products, which can be determined by analysis of the spectral characteristics, are related to: determination of color and surface texture of meat [1] active acidity of the meat (pH) [17]; determination of leanness [19]; determining the content of fat, protein, water content and dry matter [19]; determining the microbiological composition [7]; determining the freshness of meat [12]; determining the content of water, salt and the water activity of ham, sausages [24], etc.

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C. Evaluation of food quality indicators using systems for formation and analysis of hyperspectral images

Hyperspectral analysis systems (HSA) found relatively few applications in solving various tasks related to the assessment of the QS of dairy products. Published analyses are related to the possibilities of defining the content and distribution of fat and protein, casein, lactose, to identify the type of dairy product, the presence of foreign fat and other [16].

Hyperspectral analysis systems have found wide application in non-destructive analysis and evaluation of QS of meat and meat products. Published studies are related to the determination of: color characteristics, surface texture and active acid [6]; the composition of the meat and meat products [18], the contents of the different components, such as proteins, nitrogen's, water content, dry matter, etc., the microbiological composition, water activity, the freshness of the product and other [18]; determining the microbiological composition [22], determination of leanness [10], etc.

D. Summary

Based on the review and analysis of published research results related to the evaluation of QS of food products by modern optical methods, it may be pointed that an approach for complex, express, automated and nondestructive evaluation of the quality and safety of the investigated foodstuffs, based on modern optical methods for forming and analysis of visual images, spectral characteristics and hyperspectral images, and fusing the results of these analyzes is not proposed.

IV. MATERIALS AND METHODS

A. Formal description of the investigated objects by fusing data from color images, spectral and hyperspectral characteristics. Representation by weighted properties.

The complex evaluation of the investigated products is based on formal descriptions by properties, associated with visible features, the composition and distribution of features on the surface of the object. Within the frames of the investigation the main formal description of the investigated objects is based on a vector of properties of the form:

$$X = \left(m_1 \cdot x_1, m_2 \cdot x_2, m_3 \cdot x_3, \ldots, m_n \cdot x_n\right)^t \quad (1)$$

where the components x_i provide essential physical and chemical characteristics of the object related to its quality and safety, while m_i are weight coefficients, related to each of the characteristics. In summary, the features x_i can be presented in the following three groups:

- Characteristics associated with visible features and derived from color images of the products examined;

- Characteristics associated with visible features and the composition derived from spectral characteristics of the products examined;

- Characteristics associated with the distribution of features on the surface of the investigated objects derived from hyperspectral images.

B. Why to use this kind of formal presentation of the investigated objects?

The main idea is the features x_i to retain its physical nature, to present not mathematical abstractions, but certain characteristics of objects which are understandable to the experts. Furthermore, such description provides a comprehensive presentation of objects through a variety of characteristics, visible, and related to their composition, concerning both specific individual areas and the entire surface of the object studied. This kind of formal representation allows individual features to be ranked and weighted, depending on the context of the problem.

C. Why weighted features, rather than equivalent features?

Few considerations that support the idea of weighing the features x_i will be given:

- When solving similar tasks a man intuitively separates essential from non-essential details, i.e. he ranks the characteristics of an object by their importance;

- Larger values of m_i will determine a stronger presence of the component in the formal description of the object, i.e. the relevant feature will have greater significance for solving task. The suitable choice of the weights of the features may increase or reduce the significance/impact of certain features over the formal description of the investigated objects, and therefore the outcome of categorization;

- Arranging the components of the vector descriptions allows reducing the impact of certain features, whose values change significantly within a given category and are measured/determined with great uncertainty.

D. Evaluation of feature weights m_i.

Several options for selecting the values of the weighting coefficients m_i are proposed:

Option 1. The value of m_i is determined depending on how the change of corresponding feature influence to the sensitivity of the description to the change of that feature. It is measured by the change in position (distance D_{xp}) of the sample in relation to the prototype in the feature space of the samples. Quantitatively this relationship can be represented by the expression:

$$m_{iD} = k_D = {D_{xp}} \Big/ {D_{xp\max}} \quad (2)$$

where D_{xpmax} represents the maximum possible deviation of the position of the individual sample X from the prototype due to the change of feature.

Option 2. The value of m_i is determined depending on the dispersion/accuracy of the features within the category. It is natural to assume that the features with lower accuracy (higher dispersion values) need to be involved with a smaller weighting in the description of the object, i.e., the size of the weighting factor must be inversely proportional to the variance or mean square deviation s_i:

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$$m_{is} = 1 / (1 + k_s \cdot s_{in}) \quad (3)$$

where k_s is a factor determining the sensitivity of m_i to s_i and s_{in} is a value of s_i normalized to the maximum value of s.

Option 3. The value of m_i is determined depending on the inaccuracy ε_i of the measurement/determination of the corresponding feature:

$$m_{i\varepsilon} = 1 / (1 + k_\varepsilon \cdot \varepsilon_{in}) \quad (4)$$

where k_ε is a factor determining the sensitivity of m_i to ε_i and ε_{in} is a value of ε_i normalized to the maximum value of ε.

The choice of the option for determination the weights of the features depends primarily on the specific conditions, under which the problem for the categorization of the investigated products is solved. If the product characteristics are amended in a relatively wide range, Option 2 is more appropriate. If the product characteristics are measured/determined by a relatively large error, it is more appropriate to use Option 3 for determination of the weights m_i.

E. Extraction of specific features of the investigated products.

1) Feature extraction from color images

Different zones that are subject of interest can be extracted by analysis of color images and their area as well as ratios of areas can be calculated. They can be used to solve various tasks, such as:

- Determination the percentage of areas with meat and fat in pieces of meat or bacon, or

- Determination the degree of spoilage of milk product by determining the extent of contamination with mold and yeasts.

To determine the areas of specific zones on the surface of the investigated products, the color image is converted to binary image, from which, by well-known binary image analysis techniques, the area of the zones is evaluated [16]. Three approaches are used to convert the color image to binary: 1. Binarization by passing through a gray level image and setting a global threshold T; 2. Direct binarization by analyzing the color of the pixels and setting a threshold of chrominance $\Delta RGB = d = \mathrm{sqrt}\,(\Delta R^2 + \Delta G^2 + \Delta B^2)$, where R, G and B are color components from the RGB color model; 3. Combined binarization.

The first two approaches for binarization are well known and described in many literature sources. Unlike the published results in which it is claimed that on the basis of these methods certain morphological characteristics of the different areas of the investigated products can easily and relatively precisely be determined, and they can be used for assessment of variety of properties associated with the QS of these products, the studies did not confirm this fact for the following main reasons:

- The intensity of the pixels and the color of the different zones in the investigated products depend on extremely large number of factors;

- Color characteristics and intensity of the pixels significantly change during storage (particularly under the conditions of experiment);

- Due to humidification of muscle fibers in the fresh meat the received by CVS color characteristics of zones with meat and fat are very close and difficult to distinguish.

Both approaches for binarization are not suitable for solving problems related to the separation of zones in the investigated product, which are characterized with significantly distinct color characteristics and intensity and with similar visible features of pixels of different zones.

This necessitated the creation of the so called method for combined binarization, which combines techniques of image analysis and analysis of spectral characteristics. This process involves a sequence of two major phases, and is characterized by the following:

- Separation of zones with distinct color characteristics is done through computer vision techniques;

- Separation of the zones with similar color characteristics, but with distinct spectral characteristics is performed by using the spectral data for the pixels in these zones. The separability of the spectral data for these zones is provided in Section 5.

2) Feature extraction from spectral characteristics.

One of the most popular methods for determination of properties of food related to their composition, are based on analysis of spectrophotometric characteristics of the investigated products. The methods for spectral analysis can be divided into two main groups: methods for qualitative and quantitative analysis.

Methods for qualitative analysis are mainly used to clarify the structure of the spectral data. Usually in spectral investigations a large amount of multidimensional data is accumulated. For example, modern spectroscopic and chromatographic methods generate several hundred values concerning one sample. By qualitative analysis methods of the data received variations in the individual parameters can be examined; sets of data that are close and carry the same information can be identified; correlations between the data can be discovered; measured values, sharply distinguished from others can be detected etc.

Usually the quantitative analysis seeks for some kind of model for the relationship between spectral data and chemical information. To make a quantitative assessment of a property or the content of a substance in the product, a so called predictive model (which is a regression model) is created, which defines the relationship between the characteristics of spectral data and the estimated quantitative characteristics, defined by reference method. The difficulty in using such models arises from the fact that the spectral data that represent the intensity of diffuse or reflected radiation passed through the sample is not a linear function of the chemical composition of the samples. Also, usually there is high degree of correlation between the data for different wavelengths.

Within the frames of the investigation the following predictive models are created:

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1. Predictive Model 1, showing the relationship between the value of the property X_i and the time (day of storage) T_i, as shown in fig. 1.

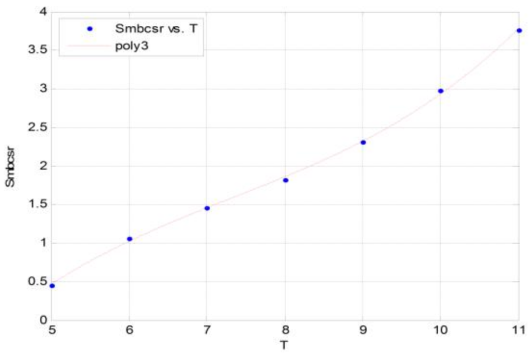


Fig. 1. Predictive model, showing the relationship between the value of the property X_i and the time (day of storage) T_i.

2. Predictive Model 2, showing the relationship between the value of the visible (or easily measurable) property X_i and the property F_i, related to the existence of the component specified in the product (e.g. number of microorganisms of a particular type), which is defined in the reference conditions. An example of such model is shown in fig. 2.

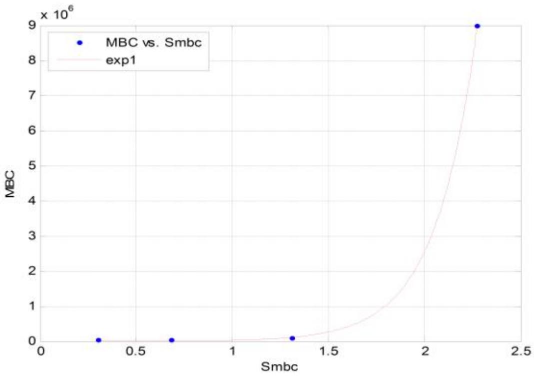


Fig. 2. Predictive model representing the relationship between property value F_i, concerning the presence of microorganisms and visible or easily measurable property X_i, for example surface area of some characteristic zone of the object.

The following predictive models for the investigated products are created:

For white and yellow cheese: change of chrominance (represented by components of HSI color model) depending on the duration of storage; changing the area S_{MBC} of colonies from molds and yeasts, depending on the storage time - the color is determined by RGB analysis (reference method); modification of the acid degree °T depending on the time of storage; modification of the acid degree °T depending on the change in color, where Smax is denoted by the maximum value of the S component of the HSI color model; changing the microbiological composition MBS depending on the color change Smax.

For meat and bacon: changing the moisture content (determined by a reference method) depending on the time of storage; changing the active acidity pH (determined by the reference method) depending on the time of storage; changing the active acidity pH depending on the moisture content.

3) Feature extraction from hyper spectral characteristics

Hyperspectral analysis integrates spatial (in a plane) information on the investigated objects, as in the images formed by a computer vision system and spectral information in each pixel of the image (fig. 3). In comparison with the conventional RGB computer vision systems, NIR spectroscopy and multispectral analysis, the hyperspectral analysis integrates spatial and detailed (in particular object zones) spectral information of the investigated objects.

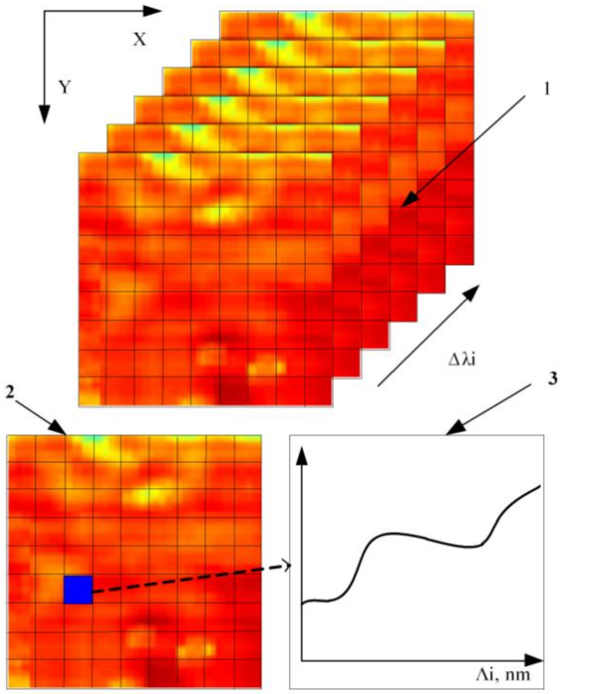


Fig. 3. Schematic representation of the relation between spectral and spatial characteristics in hyperspectral imaging: 1 – set of images in different narrow bands Δλi; 2 – plane image (X-Y) from one bandwidth Δλi; 3 – spectral characteristic of one particular pixel from the plane image for Δλi.

It is important to emphasize the following basic options of hyperspectral analysis systems that qualitatively distinguish them from computer vision and spectral analysis systems:

1. Presentation of the spectral characteristics in narrow non-overlapping spectral bands. This suggests that the investigation could be done as in the whole spectral range of the hyperspectral camera and in particular individual frequency bands.

2. Direct determination of the spectral band, in which given property can best be identified. This is a significant advantage, which allows predictive models of a property to be formed not in the whole spectral range of the device, but only in a narrow band range which is most sensitive to the corresponding property.

3. Analysis of the entire surface of the object (analysis of each pixel / local area of the image of the object). This feature allows one hyperspectral analysis system to perform analysis of objects with heterogeneous surface and to realize one of its most characteristic advantages, namely to integrate spatial

information about investigated objects and spectral information in each pixel of the image.

In this investigation hyperspectral characteristics are formed by converting a spectrophotometric characteristic of the investigated object obtained by the spectrophotometer operating in visible or NIR spectral range. Hyperspectral characteristic is obtained by dividing the spectral characteristic in multiple non-overlapping spectral bands.

The following tasks are solved by hyperspectral characteristics analysis: 1. Determination of the minimum number of spectral bands necessary for effective separation of the spectral data for different classes of objects, and 2. Determination of the spectral band with maximum separability of data classes.

F. Assessment of the separability of data classes

Separability of data for different areas (e.g. areas with meat, fat and bone tissue in pieces of meat) on a certain day of the storage of the product, and for the same area on different days of storage of the product is a major criterion for the correct classification both with regard to composition of the product and of its freshness. It is evaluated using data derived from spectral and hyperspectral characteristics of the investigated products. The separability is quantitatively assessed by the overlap error ε_{pr}% (the ratio of incorrectly classified examples to the total number of examples). The separability determination was made by two methods: LDA, which implements linear separability, and kernel version of SVM, which satisfies the conditions for linear separability of the classes of data.

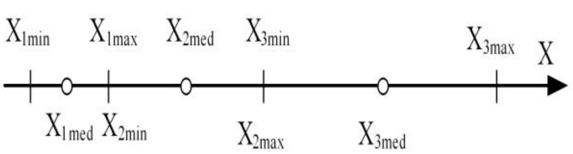
The separability of the data is examined in two variants: 1. When the data for the features derived from the spectral characteristics of the entire spectral range of the spectrophotometer is used, and 2. When using the data for the features, derived from the selected frequency bands, of which the spectral characteristic of the device is divided.

G. Categorization of the investigated objects in groups of quality. Interval, prototype and kernel models for categorization.

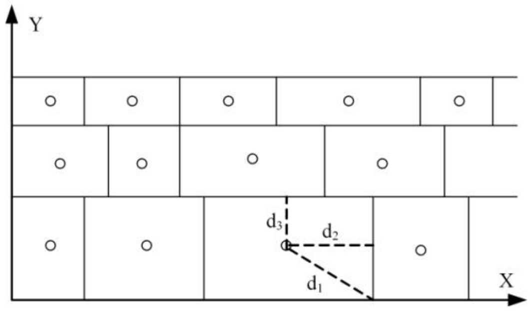
When solving the problem for categorization of the investigated products in groups of quality, the possibility of applying the following models of categorization is examined:

1) Interval models.

When solving tasks related to the categorization of food products the so called interval assessments are traditionally used. They are illustrated for one-dimensional and two-dimensional descriptions in fig. 4a and b.



a)



b)

Fig 4. Graphical interpretation of interval assessments.

The network architecture, presented in fig. 5, is used in the investigation for implementation of interval assessments.

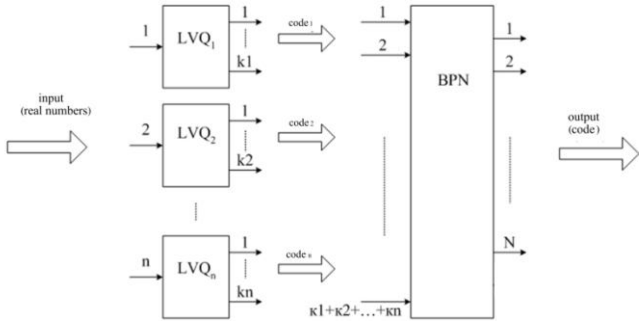


Fig. 5. Network architecture, defining class areas of in the form of parallelepiped (CCNN)

The classifier structure, which defines class areas of in the form of parallelepiped, is shown in fig. 5. It is composed of two types of neural networks - LVQ and BPN. The first layer includes n (n is the dimension of the input vector) LVQ networks [16]. They have one input corresponding to one of the components of the input vector and $k_i = m_i + 1$ number of outputs, where m_i is the number of significant intervals along the axis x_i, determining the projections of the classes to the axis x_i.

The second layer consists of a back - propagation network which has N output neurons (N is the number of groups of samples). The network group the output vectors (ranges), formed by the first layer in necessary classes and encode them appropriately.

2) Prototype models

The prototype assessments define specific conditions (prototypes), described with specific characteristic vectors. In multivariate descriptions the prototype assessments set in the feature space points, corresponding to the characteristic vectors that represent the prototypes. In 2-D space (Fig. 6) they create areas of the kind of polygon with sides, corresponding to the medians of the specific pairs of neighboring prototypes.

In this option the classification task is reduced to a task of approximation of the area of each of the classes/categories by one radial basic element (RBE) - Fig. 7. Radial basic elements define Euclidean distances of input vectors to the categories prototypes and weigh these distances by using Gaussian function

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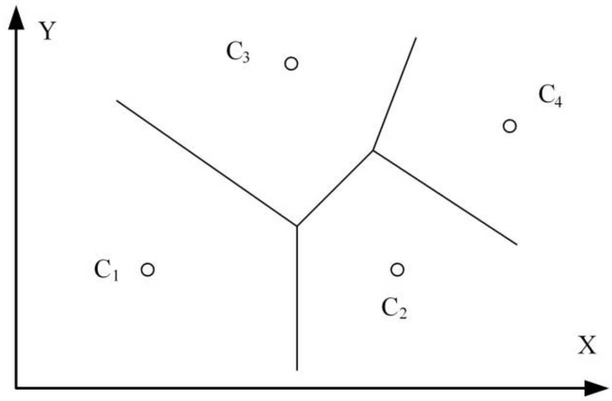

Fig 6. Graphical interpretation of prototype assessments

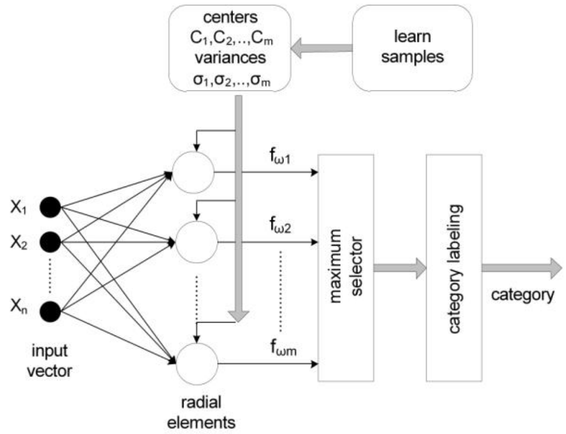

Fig. 7. Classifier architecture with spherical radial basis elements.

3) *Kernel models*

The method of kernel models is suitable for cases when there is a small number of training data and requires a simple distribution function to be included at a point corresponding to an observation. After that all these functions are accumulated and the result is an estimate of the total probability density. Most often, Gaussian function are selected as kernel functions.

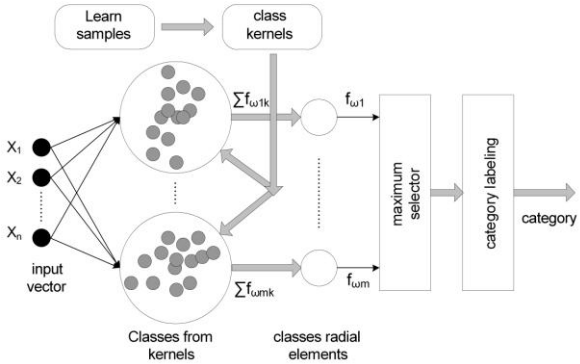

Fig. 8. Network architecture, presenting the kernel estimates approach.

A variant of a classifier for class region approximation by RBEs is realized and its architecture is shown in fig. 8. The accumulation of patterns (corresponding to a training data) in an area in feature space corresponding to a sample of patterns from a given class, creates a general distribution of that class. When an unknown input vector must be classified in one of the created classes/categories, the weighted distance to all the kernels of the respective classes is estimated.

H. *Description of the system, including CVS and spectral analysis systems. Formation of hyperspectral characteristics.*

A system for formation and analysis of visual images, spectral and hyperspectral characteristics, presented on fig. 9, was developed in Ruse University by a team from the Department of Automation and Mechatronics.

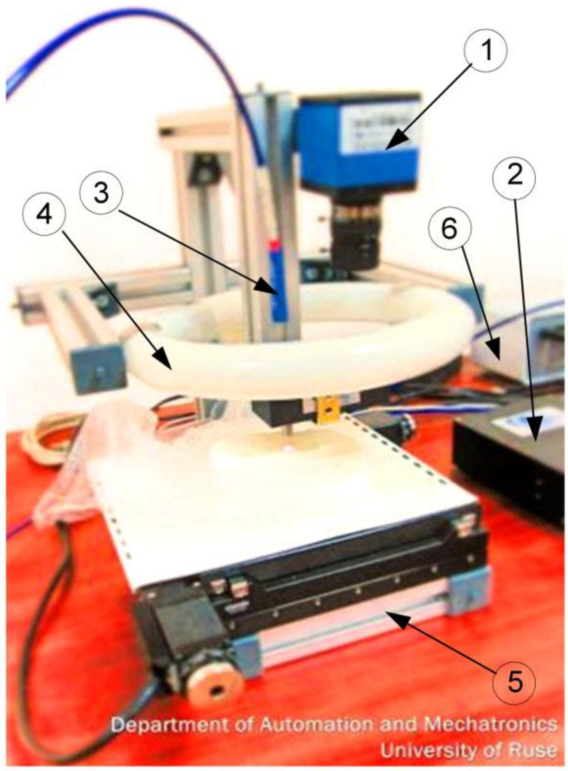

Fig. 9. Hyperspectral imaging system based on point scanning: 1 – RGB camera DFK 31AU03; 2 – QE65000 spectrophotometer; 3 – spectrophotometer probe; 4 – illumination system; 5 – 8MTF-102LS05 XY motorized scanning stage; 6 – 8SMC4-USBhF stage motion controller.

What are the main characteristics of the system?

1. It can form color images of the investigated objects, the spectral characteristics of the diffuse reflection in a small area of the object and hyperspectral images in separate small areas (pixels) in lines of pixels as well as in the plane of the object. This is performed using XY motorized scanning stage (5) equipped with a controller (6). The investigated object is placed over the stage. By controlling the motion of the stage the spectrophotometer probe (3) could be placed over individual pixels, separate important object areas or the whole object surface could be scanned.

2. The second specific feature is related to the way hyperspectral characteristics of individual pixels are obtained. The spectrophotometer forms spectral response across the overall spectral range of the instrument in each pixel. After that the neighboring points of the spectral

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characteristic are aggregated together using a specific algorithm, in order to obtain hyperspectral characteristic, consisting of various non-overlapping spectral bands. The number of frequency bands (frequency ranges $\Delta\lambda_i$) can be set in advance, or the minimum required number of bands can be formed, based on a certain criterion, which within this study is related to the separability of the data classes (linear or non-linear separability, achieved respectively by LDA and kernel SVM classifiers). The results presented in sections below refer to the frequency band for which the best data separability is achieved.

V. RESULTS FOR SEPARABILITY ASSESSMENT, BASED ON IMAGE ANALYSIS, SPECTRAL AND HYPERSPECTRAL ANALYSIS

The possibility of separation of the following areas of the investigated products, for a particular day of storage, is examined:

- Cheese and yellow cheese: areas with and without colonies of molds and yeasts;
- Meat and bacon: areas with meat and fat tissues.

For each of the characteristics, presented in Section II, the change in different days of storage of the product is examined.

A. Assessment of area separability using image analysis.

In the framework of this study, an attempt was made to separate the above-mentioned fields, by the first two binarization methods, described in Section IV, subsection E1. For both methods, the error in determining the area of individual areas reached significant levels (tens of percent), which is not acceptable even for objects with significantly changing color characteristics. Color characteristics, even for one area, for example the area of meat tissue in pieces of meat or bacon, vary widely, and depend on a number of factors. These are for example the age of the animal on whether the meat is normal or is pale, soft, watery, the duration of storage, even the geographical area in which the animal is kept. Color characteristics of areas with colonies of fungi, yeast and mold in dairy products also vary considerably.

Unacceptably large errors for separation of the investigated areas were received as for the identification of various areas on a certain day of the storage of the product, and in assessing data separability for the same area on different days of storage.

B. Investigation of areas separability using spectral characteristics analysis across the overall spectral range of the instrument.

The possibility for separation of the spectral data for different areas, presented with the first three principal components will be illustrated by one of the investigated objects: structural bacon with meat and fat tissues. To extract the features of spectral characteristics and to reduce the dimensionality of the spectral data, PCA method is used, where the number of principal components ranged from 3 to 10. The study was conducted in VIS and NIR spectral ranges. Table 2 present the overlap errors ε_{pr}% for data classes, described by principal components, obtained from the spectral characteristics of areas with meat and fat tissues in overall spectral range of the spectrophotometers. The data separability for a same area in different days of storage is investigated. Forty samples of bacon are analyzed, where for every area spectral characteristics in 3 different points are measured.

Table 2. Overlap errors for bacon in two different days

Day	Error value, ε_{pr}%			
	VIS		NIR	
	Meat tissues	Fat tissues	Meat tissues	Fat tissues
1vs2	7.37	2.11	24.21	8.42
2vs3	17.34	44.48	5.618	2.13
3vs4	44.56	44.56	4.49	2.25
4vs5	45.35	48.87	0	0
5vs6	36.14	38.37	0	0
6vs7	39.14	40.96	34.94	46.99
1vs3	16.84	22.11	1.05	1.053
3vs5	30.34	41.57	0	0
5vs7	40.24	43.37	0	0

The investigation of class separability by empirical data for VIS characteristics from the overall spectral range shows, that the average error values for meat tissues in bacon vary between 7.4% and 45.4%, while for fat tissue – between 2.1% and 48.9%. The investigation of class separability by empirical data for NIR characteristics from the overall spectral range shows, that the average error values for meat tissues in bacon vary between 0 and 34.9%, while for fat tissues – from 0 to 47%. The results for overlap error examination during the investigation of data separability for different areas on a same day of storage are similar.

C. Investigation of areas separability using data analysis in selected frequency bands of the hyperspectral characteristics.

The overlap errors ε_{pr}% for data classes of principal components, obtained from the hyperspectral characteristics of meat and fat tissues in bacon are presented in Table 3. The data separability for a same area in different days of storage is investigated.

The investigation of class separability by empirical data for VIS characteristics in selected frequency band shows, that the average error values for meat tissues in bacon vary between 0 and 0.47%, while for fat tissue – between 0 and 0.45%. For meat these values are: for meat tissues–from 0.22% to 0.42%, for fat tissues – from 0.12% to 0.42%. The investigation of class separability by empirical data for NIR characteristics in selected frequency band shows, that the average error values for meat tissues in bacon vary between 0 and 0.39%, while for fat tissues – from 0 to 0.43%. For meat these values are: for meat tissues–from 0.29% to 0.33%, for fat tissues – from 0.34% to 0.37%.

Table 3. Overlap errors for bacon in two different days

Day	Error value, ε_{pr}%	
	VIS	NIR

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	Meat tissues	Fat tissues	Meat tissues	Fat tissues
1vs2	0	0.06	0	0
2vs3	0	0.04	0	0.40
3vs4	0	0.14	0.13	0.24
4vs5	0.05	0.17	0.14	0.44
5vs6	0.25	0.45	0.23	0.38
6vs7	0.10	0.32	0.07	0.41
1vs3	0.02	0.20	0.01	0.20
3vs5	0.03	0.28	0.03	0.35
5vs7	0.30	0.47	0.26	0.45

The maximum overlap error for the two classes of data, obtained from hyperspectral characteristics, does not exceed 0.47% in visible spectral range and is up to about 0.43% in near infrared spectral range.

The results for areas with meat and fat tissues in meat slices are similar.

Compared with overlap errors obtained using data derived from the spectral characteristics of the samples throughout the overall spectral range of the device, the overlap error of the two classes of data derived from selected bands of hyperspectral characteristics, decrease by nearly two orders of magnitude.

Table 4 presents the overlap errors, obtained during the investigation of the data separability for different areas in a same day of storage. The minimal number of frequency bands in hyperspectral characteristics of the investigated objects is denoted with *n*, while *N* denotes the number of the spectral band with the best separability.

Table 4. Class separability for bacon in a particular day of storage: cl1 – meat tissues, cl2 – fat tissues

	VIS spectral range					
Classifier	**LDA**			**SVM-K**		
Day	**n**	**N**	**ε_{pr}%**	**n**	**N**	**ε_{pr} %**
	cl1 vs cl2					
0	3	3	0-0.1	6	6	0-0.06
3	4	4	0-0.16	3	3	0-0.12
6	7	7	0-0.14	20	9	0-0.12
	NIR spectral range					
Classifier	**LDA**			**SVM-K**		
Day	**n**	**N**	**ε_{pr}%**	**n**	**N**	**ε_{pr}%**
	cl1 vs cl2					
0	28	15	0.05-0.15	55	30	0.08-0.16
3	3	3	0.03-0.1	35	9	0.02-0.1
6	43	11	0.02-0.12	22	7	0.06-0.13

When using data from visible spectra, PCA model for data representation and LDA classifier, the values for *n*, *N* and ε_{pr} vary from 3 to 7, 3 to 7 and from 0 to 0.16% respectively. When using kernel SVM classifier these values vary from 3 to 20, 3 to 7 and from 0 to 0.012% respectively. If near infrared data, PCA model and LDA classifier is used, these values vary from 3 to 43, 3 to 15 and from 0.05 to 0.15% respectively, while when kernel SVM classifier is used, the values change from 22 to 55, 7 to 30 and from 0.08 to 0.16%. These results concern classification of class1 against class2. The results for the others pairs of classes (class1 vs class3, class2 vs class3) are similar.

VI. CONCLUSION

Based on the investigations and the results obtained the following main conclusions can be made:

1. The analysis of color images of the investigated objects gives the most incorrect results when evaluating separability of different areas from the analyzed objects. This is due to the fact that the color characteristics of the different areas vary widely and depend on a number of factors that are not related to the conditions of the experiment. However, this method is most suitable for the evaluation of quantitative characteristics of the regions under assessment, for example, their area, which is one of the important quantitative characteristics of products quality. The precise separation of regions with similar color characteristics but with different composition can be carried out by the proposed method of combined binarization.

2. The investigation of class separability using empirical data in the overall spectral range of the device show, that the overlap error for the two classes of spectral characteristics for bacon vary from several percent to about 49% for visible range and to about 47% for near infrared range. The results for the overlap errors when the separability of the data for different regions on a same day of storage is investigated are similar.

3. The investigation of class separability using empirical data from selected frequency bands show, that the maximum overlap error for the two classes of hyperspectral characteristics does not exceed 0.47% for visible range and 0.43% for near infrared range. The results for the overlap errors when the separability of the data for different regions on a same day of storage is investigated are similar.

4. There is a significant difference between mean values of errors obtained on the basis of spectral data for the entire spectral range and errors obtained using spectral data of the selected frequency bands. The difference in the classification accuracy is two orders of magnitude. These very low values of the overlap errors for data classes from hyperspectral characteristics are received due to the fact that the class separability is accessed in a narrow spectral band, instead of in the entire frequency band of the device. This is perhaps one of the most important advantages of the hyperspectral analysis to classic spectral analysis.

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