Model-based approach for assessment of freshness and safety of meat and dairy products using a simple method for hyperspectral analysis

MIROLYUB IVANOV MLADENOV

Summary
A model-based approach for assessment of freshness and safety of meat and dairy products is proposed. In contrast to traditional methods for assessment of food quality, this approach can be used for rapid and non-destructive evaluation „on site", i.e. in food shops, warehouses, catering services or homes. Freshness and safety are evaluated using three types of regression predictive models. A new simple method for hyperspectral analysis is proposed. Extraction and selection of the food quality features are supported by this method. It avoids the basic limitations of the hyperspectral imaging technologies for evaluating food quality and safety. It reduces sufficiently the number of bands of the hyperspectral characteristics in comparison with the traditional methods used in hyperspectral imaging. The method uses a new criterion for bad selection. The complex optical system for light dispersion in the hyperspectral imaging sensor could be replaced with an optical system of a traditional spectrophotometer by using this method. The food quality features are extracted from the spectral characteristics of the spectrophotometer and selected frequency bands of the hyperspectral characteristics. The separation error between different spectral data classes is evaluated. It sufficiently decreases when the spectral data from a selected frequency band are used.

Keywords
model-based approach; hyperspectral analysis; food safety; predictive model

Methods for assessment of food quality, freshness and safety

Food quality and safety are the main topics of many investigations in the subject domain. This is not accidental. According to the World Health Organization, food quality and safety are the key measures of quality of life [1]. Food is the basis of all important processes in the human body.

Traditional methods for assessing food quality and safety are sensory evaluation, chemical, and microbiological analyses. These are laboratory methods that require specific conditions, equipment, materials, and personnel with relevant training. They are not suitable for "on-line" monitoring and rapid evaluation of food quality and safety "on site", i. e. in food shops, warehouses, catering services or homes, where the food is not always stored in conditions recommended by the manufacturer.

As an alternative to traditional methods, methods for rapid and non-destructive evaluation of food quality are applied in recent years. Among them, promising methods are the non-contact optical methods based on colour images, spectrophotometric and hyperspectral analysis (HSA). In this study, HSA is used to evaluate freshness and safety of widespread food products such as white brined cheese and kashkaval from cows' milk, pork meat and bacon during their storage under conditions different from those recommended by the manufacturer.

Quality, freshness and safety assessment using hyperspectral images

One of the modern approaches for assessment of food quality is based on the analysis of hyperspectral imaging (HSI). HSI is a core topic of many studies. It is considered as a powerful and rapidly growing method for non-destructive food quality analysis and control. It could be used to simultaneously obtain large amounts of spatial and spectral information on various objects [2].

Mirolyub Ivanov Mladenov, Department of Automatics and Mechatronics, Faculty of Electrical Engineering, Electronics and Automation, University of Ruse "A. Kanchev", 8 Studentska, 7017 Ruse, Bulgaria, E-mail: mladenov@uni-ruse.bg

Basic principles and applications of HSI for quality evaluation of agro-food products were reviewed by SICHE et al. [3], WU and SUN [4, 5], ELMASRY et al. [6], HUANG et al. [7] and KAMRUZZAMAN et al. [8], who reported that near infrared (NIR) HSI technology is mainly used for determining the composition of a variety of food products, such as meat and meat products, fish, milk, cheese, fruits, vegetables, legumes, cereals, egg products, as well as for the evaluation of their major quality and safety indicators. Some typical examples of the application of HSI for assessment of various features associated with the food quality of dairy products may be indicated [3, 6, 9]. Food quality attributes of dairy products, which can be determined by analysis of hyperspectral characteristics (HSC), are related to surface colour characteristics and their change during storage, the appearance of colonies of filamentous fungi and yeasts of microbial contamination, Thorner degree °*T* and pH [9]. Main features of meat and meat products, which can be determined and predicted by analysing HSI, are related to pork and beef quality parameters and attributes [10–12], poultry carcasses, fish fillets [11], freshness of meat products during storage [13], red meat colour [14], microbial contamination [15], fish microbial spoilage [16], tenderness of beef steak [17, 18], categorization and authentication of red meat [8], contamination, adulteration and authenticity of meat, poultry and fish [19], moisture content [20], protein content of processed pork meats [21] and microbial spoilage of beef [22].

Some of these parameters and attributes, like colour characteristics, appearance of colonies of filamentous fungi and yeasts, microbial spoilage, water content, active acidity pH, Thorner degree °*T* and others concern the product freshness and safety, too [9].

Basic disadvantages of hyperspectral imaging technologies

In spite of the significant potential of HSI technologies, some disadvantages could be discussed:

1. In a typical hyperspectral camera, the spectral characteristics in every pixel are obtained physically, using a complex optical system for light dispersion. HSI sensors are complex and costly sensors.
2. There is a huge number of non-overlapping frequency bands. HSI typically provides images with hundreds of narrow contiguous spectral channels. The spectral information provided by HSI is very huge in comparison with other classes of remote sensing images [23]. Processing and using the hyperspectral data (HSD) are considered as a challenging task because of their high dimensionality. The computational complexity increases if all the bands are used for processing and it also takes lots of time to process [23].
3. The accuracy of separation of the spectral classes has to be evaluated in every band.
4. There is no reason for using HSI sensors and HSI technologies for investigation of objects or areas with homogenous surface and homogenous content. To analyse such kind of objects or areas, traditional spectrophotometry can be used. When evaluating quality, freshness and safety of food products like meat and dairy products, the number of samples is limited because of the nature of the investigated products. The comparatively small number of samples or the number of points in one spectral band of HSC, respectively, impose additional limitations of the maximum number of bands to which the spectral characteristics are divided [9].
5. If principal component analysis (PCA) is used for dimensionality reduction of HSD, the maximum number of points in one spectral band cannot be smaller than the number of principal components (PC). If this number is 10 and the number of points in the overall spectral range of the spectrophotometer is 1000, then the maximum number of bands is 100.
6. If HSD is used for classification (as in this study) and an insufficient number of points for each spectral class is available, the phenomena illustrated in Fig. 1 arise. Fig. 1 shows a typical example of the variation of the overlap error ε_{ov} (in percent) between two classes in relation to the number of bands to which the initial spectral characteristics are divided. The sup-

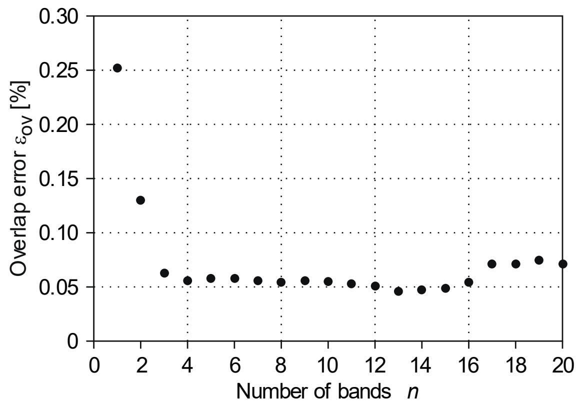

Fig. 1. Variation of the overlap error in relation to the number of bands.

port vector machine (SVM) classifier is applied to separate the spectral data classes. The task is to find the band with the minimum value of ε_{ov}. The accuracy of separation is evaluated by the overlap error ε_{ov} between the spectral data classes (data from different areas after one day of storage and in one area on various days of storage). The overlap error is actually the classification error rate, which is the ratio of the relative number of incorrectly classified spectral data (which belong to a spectral class, but they are classified to another spectral class) to the total number of the spectral dataset. The overlap error starts to increase when the number of bands (to which the spectral characteristic is divided) exceeds a specific value. This result is due to the fact that when the number of bands is increased, the number of points in each band is decreased. When the length of the spectral bands decreases, PC are evaluated less precisely, the number of spectral data in the training set of the classifiers and the separation accuracy decreases, too [9].

Dimensionality reduction of hyperspectral data

In order to reduce the dimensionality of HSD, the redundant data can be eliminated by using the dimensionality reduction technique (DRT). Using an appropriate DRT, the highly redundant data could be eliminated without losing much significant spectral information [23]. DRT is to be applied before HSD are used for processing, as a pre-processing step [15]. The high dimensionality of HSI data can map to lower dimensions without losing much of spectral features provided by the original HSD.

The methods used for dimensionality reduction can be grouped into two types. The first group is based on transformation techniques. The second group uses the band selection technique (BST) [24–28]. Various methods such as PCA, discriminant analysis, wavelet transform, minimum noise fraction transform, non-parametric weighted feature extraction and spectral mixture analysis, Fourier transform spectral imaging (FTSI) or partial least squares (PLS) are used to reduce data redundancy or to extract specific information from HSI. The main aim of BST is to find a minimum subset of the original data containing the most useful information about the object, removing redundant, irrelevant or misleading spectral features from HSD, without losing their physical meaning.

PCA and discriminant analysis methods are widely used for feature extraction and selection [29]. These two methods are used and discussed in this study. PLS and FTSI are other often applied methods for feature extraction and selection. The FTSI technology has the advantages of a high level of detection sensitivity and light throughput. The present FTSI methods use point-by-point scanning with a single detector or capture images through array detectors. This method either takes a long time or sacrifices detection sensitivity [30, 31].

Fourier transform spectroscopy is well suited for HSI [31]. Without the need for a diffractive or dispersive element to separate the light into its component wavelength bands, each wavelength is monitored for the entire duration of the scan. This increases the integration time over which each wavelength band is measured.

PLS is able to reduce sufficiently dimensions of the feature space [32]. Its classical version is based on non-linear iterative PLC algorithm to model relations among features on the data through latent variables. Basically, new features (latent variables) are generated as a linear combination of the original feature set considering its respective classes or categories [32].

In spite of applying one or more DRT, the problem of the high dimensionality of HSD remains. The use of a DRT makes the task for real-time food quality and safety assessment more complex.

The following new approach and method are proposed in the study:

Model-based approach

A model-based approach (MBA) for assessment of freshness and safety of meat and dairy products is proposed. In contrast to traditional methods for assessment of food quality, this approach can be used for rapid and non-destructive evaluation „on site“. Freshness and safety are evaluated using three types of regression predictive models (RPM).

MBA is implemented using the following steps:

1. RPM1, which presents the relationship between the value of X_{iPCA} of the measured feature X_i and the day of storage T_i is developed. X_{iPCA} is a value of variable X_i, obtained from spectral characteristics using the PCA method.
2. RPM2, which gives the relationship between the value of property X_{iPCA} and the value of visible property X_j, is created.
3. RPM3, which presents the relationship between the values of property X_{iPCA} and easily measurable property X_k, is developed.
4. The length of storage (freshness) and the admissible length of storage (safety) are evaluated using the RPMs mentioned above.

In contrast to a traditional RPM (which gives the relation between the value of property X_{iPCA} and the respective value X_i of this property, measured by a reference method), RPM 1 presents the relationship between the value of X_{iPCA} and the day of storage T_i.

The PCA method is used to extract the quality features from spectral characteristics and to reduce the dimensionality of the spectral data.

Method for hyperspectral analysis

A new simple method for HSA is proposed. Extraction and selection of the food quality features are supported by this method. It avoids the basic limitations of the HSI technologies in the assessment of food quality and safety. This method is based on the spectral characteristics of the investigated food products obtained by traditional spectrophotometry. It converts spectral characteristics obtained in the overall measuring range of the spectrophotometer into HSC with a low number of bands.

HSCs are developed by the following procedure. It starts by dividing the spectral characteristics obtained through traditional spectrophotometry (for example, using a "point scan" spectrophotometer) into neighbouring non-overlapping spectral bands.

The procedure stops dividing the spectral characteristics if one of the following criteria is met:

– An acceptable separability ε_{ovacc} of the spectral data is detected for at least one of the spectral bands. It is a new criterion for creating a new HSC, which is not discussed in previous studies in the study area. The reason for using such a criterion is the following. There is no reason to search for a value of ε_{ov} of approximately 0.03–0.05 %, if the accuracy of obtaining the empirical data is, for example, 95–97 %. It is normally the range of the separation accuracy (presented by ε_{ov}) to correspond to the range of error of obtaining the empirical data.
– The maximum separability of spectral data classes is obtained. This is an optimization task, which is used in different studies as BST, when HSC is already obtained. In the study, this criterion is used for creating a new HSC. The separability is determined by linear discriminant analysis (LDA) and kernel SVM (SVM-K) classifiers. The main reasons for using this method are the following: (1) Instead of analysing hundreds of neighbouring frequency bands in every pixel, this method analyses HSC with a low number of bands. This number could be, for example, two. (2) The complex optical system for light dispersion in the hyperspectral imaging sensor could be replaced with an optical system of a traditional spectrophotometer.

The main goals of this study are the following:

– to propose MBA for assessment of freshness and safety of meat and dairy products;
– to propose a new method for HSA, which avoids the basic limitations of HSI technologies in the assessment of food quality and safety;
– to evaluate separability of the spectral data classes (data from various areas of the investigated food products after one day of storage, and data in one area on different days of storage), when the spectral data are obtained from the overall measuring range of the spectrophotometer and from selected frequency bands of HSC.

MATERIALS AND METHODS

Food samples and characteristics

The food products investigated in this study are widespread food products such as meat and bacon (both produced by Mekom, Silistra, Bulgaria), white brined cheese (Fig. 2A) and kashkaval from cows' milk (Fig. 2B), both produced by Bi Ci Ci Handel (Elena, Bulgaria), stored in conditions different from those recommended by the manufacturer, which are temperature 20 °C and lack of illumination.

The following main features of the investigated food products associated with their freshness and safety are analysed in this study: areas with filamentous fungi, Thorner degree °*T*, pH, water content, colour change presented by the hue, saturation, value (HSV) colour model and appearance presented by the change of the area with filamentous fungi. The spectral characteristics were obtained using the spectrophotometers QE65000 (visible spectrum) and NIRQuest 512 (NIR spectrum; both Ocean Optics, Largo, Florida, USA). The reference analyses and assessments were made in the reference laboratory (Laboratory for testing of foods, forages and biological materials, Ruse, Bulgaria). Forty samples of each product were analysed. The spectral characteristics were measured in 120 different points for each area. From the data, 70 % were used for training the classifier and 30 % for testing. The results on the separability of the spectral data classes were obtained using kernel SVM and LDA classifiers. The software procedures for image and spectra acquisition, processing, analysis and graphics presentation were developed using MATLAB Version R2013b (Mathworks, Natick, Massachusetts, USA).

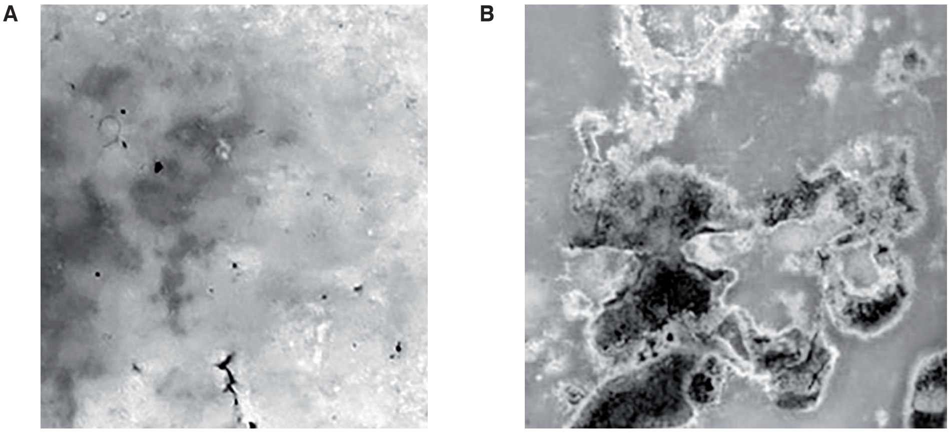

Fig. 2. Investigated products.

A – white brined cheese with colonies of fungus, B – kashkaval with filamentous fungi growing on the surface.

Model-based approach for assessment of freshness and safety

The following details have to be added to the description of MBA, presented in the introductory section. Freshness (the time or day of storage T_i) and safety (the admissible time of storage T_{iadm}) are evaluated using the following types of RPM [9]:

Regression predictive model 1 (RPM1), which presents the relationship between the value of X_{iPCA} of the measured feature X_i and the duration of storage T_i: $X_{iPCA} = f(T_i)$.

This predictive model gives the possibilities to predict the changes in the food quality features in the future and to evaluate the admissible length of storage of food products.

The procedure for developing the RPM1 consists of the following steps (the procedure is described in detail in our previous study [9]):

- development of graphical and analytical models of the equation $X_{iREF} = f(T_i)$, where X_{iREF} is the value of the variable X_i, which is measured by a reference (standard) method, during all days of storage;
- development of graphical and analytical models of the equation $X_{iPCA} = f(X_{iREF})$, i.e. the reference/traditional predictive model;
- for a particular value of X_{iPCA}, a respective value of X_{iREF} is calculated from the analytical model $X_{iPCA} = f(X_{iREF})$ and the value of T_i can be obtained from the model $X_{iREF} = f(T_i)$;
- The graphical and analytical models $X_{iPCA} = f(T_i)$ are developed.

Regression predictive model 2 (RPM2), which shows the relationship between the value of property X_{iPCA} and the value of visible property X_j.

The following procedure for developing predictive model 2 is used:

- the regression models $X_{iPCA} = f(T_i)$ and $X_{jREF} = f(T_i)$ are developed using the procedure for creating the predictive model 1 (vide supra);
- using these two models, the resulting model $X_{iPCA} = f(X_{jREF})$ could be created.

Regression predictive model 3 (RPM3), which presents the relationship between the values of property X_{iPCA} and easily measurable property X_k, which is defined using a reference method.

The RPMs are assessed by the following statistical parameters: mean squared error (*MSE*), standard deviation (*SD*), explained sum of squares (*ESS*), standard error (*SE*) and Pearson correlation coefficient (*PCC*).

Measuring the value of the property X_k

The current value of the property X_k can be evaluated "on site" by a portable spectrophotometer, for example, the SCiO Food Sensor (Consumer Physics, Herzliya, Israel). According to the producer the device would allow users to scan different objects and materials (dairy, meat, fruit and vegetables) and get instant information about their chemical makeup.

If the physical value of a property X_k is measured by an appropriate portable spectrophotometer, the respective value of X_{iPCA} can be evaluated using the analytical model $X_{iPCA} = f(X_{iREF})$ (traditional predictive model). Using this value in the model $X_{iPCA} = f(T_i)$, the respective value of T_i can be assessed. This value represents the freshness of the food product. Safety (admissible time of storage T_{iadm}) can be evaluated, if the admissible value of X_j is known.

Evaluating freshness and safety

By using a specific value of a variable X_i, it is easy to evaluate the length of storage T_i (freshness). The predictive models $X_{iPCA} = f(X_{iREF})$ and $X_{iPCA} = f(T_i)$ can be consecutively applied for this purpose. To evaluate the admissible length of storage T_{iadm} (safety), we have to replace X_{iREF} with the admissible value of the respective feature X_{iadm} in the predictive model $X_{iPCA} = f(X_{iREF})$. Then using the $X_{iPCA} = f(T_i)$ model, T_{iadm} can be determined.

Method for hyperspectral analysis

The following details have to be added to the description of the method for HSA, presented in the introductory section. HSCs are developed using the following procedure. The spectral characteristics obtained through traditional spectrophotometry (for example, using a „point scan" spectrophotometer) are divided into a number of neighbouring non-overlapping spectral bands (n). This number n can vary from 2 to 10, 20, 30, 40, 50 or 100. The procedure can be implemented in two variants:

- Variant 1. The procedure starts dividing the spectral characteristics into 2, 3, 4, 5,….., n parts. At every turn, the algorithm checks the separability of the spectral data of different areas (presented by PCs). The procedure stops dividing the spectral characteristic when an acceptable separability of SD is detected at least for one of the spectral bands. The band with number N, in which the minimum error is obtained in the investigated HSC, is detected, too.
- Variant 2. The spectral characteristics are divided into a priori defined number of non-overlapping spectral bands (for example, $n = 100$). After that, the separability of the spectral data is assessed in each frequency band. The band with number N, in which the maximum separability is obtained, is detected.

The PCA method is used to extract the quality features from spectral characteristics and to reduce the dimensionality of the spectral data. The relatively small value of the overlap error ε_{ov} when the number of PCs is 10 indicates that PCs include a sufficiently large part of the input data to obtain sufficiently precise estimates [9].

RESULTS AND DISCUSSIONS

Quality features

The following main characteristics of the investigated products were analysed in this study:

- for cheese and kashkaval: surface colour characteristics and their change during storage; areas of filamentous fungi; Thorner degree °T, pH and their changes during storage, and the appearance presented by the change of the area of filamentous fungi.
- for pork meat and bacon: surface colour characteristics, water content and Thorner degree °T, pH and their changes during storage.

Regression predictive models

Some examples of RPM1, RPM2 and RPM3, which were used for assessment of freshness and safety, are presented below.

An example of RPM1 is presented in Fig. 3. It has the following equation:

$$\mathrm{pH} = 0.003T^2 - 0.073T + 6.216 \tag{1}$$

where T is the duration of storage, expressed in days. The predictive model is polynomial, second degree, with the following statistical assessments: $MSE = 9.37 \times 10^{-4}$, $SD = 7.99 \times 10^{-2}$, $ESS = 7.89 \times 10^{-2}$, $SE = 3.06 \times 10^{-2}$ and $PCC = 0.99$.

An example of RPM2 is shown in Fig. 4. The equation is:

$$MBC = (4.1701 \times 10^5)S_{MBC}{}^3 - (1.1219 \times 10^6)S_{MBC}{}^2 + \\ + (9.4369 \times 10^5)S_{MBC} - (2.0507 \times 10^5) \tag{2}$$

where MBC is the microbiological contamination (colonies of filamentous fungi) expressed as number of cells in the investigated sample (40 g), measured by a reference laboratory, S_{MBC} is the visible area with microbiological contamination in the RGB image, expressed in a number of pixels. The predictive model is polynomial, third degree, with the following statistical assessments: $MSE = 1.54 \times 10^{-17}$, $SD = 6.75 \times 10^{13}$, $ESS = 6.75 \times 10^{13}$, $SE = 1.30 \times 10^{-9}$ and $PCC = 1.00$.

The value of a visible property X_j (S_{MBC}) can be evaluated by an appropriate procedure using an image processing technique.

An example of RPM3 is shown in Fig. 5. The equation of this model is:

$$\mathrm{pH} = 4.652W^3 - 0.015W^2 + 0.896W - 10.86 \tag{3}$$

where W is the water content, expressed in percent. The predictive model is polynomial, third degree, with the following statistical assessments: $MSE = 6.19 \times 10^{-28}$, $SD = 0.38$, $ESS = 0.38$,

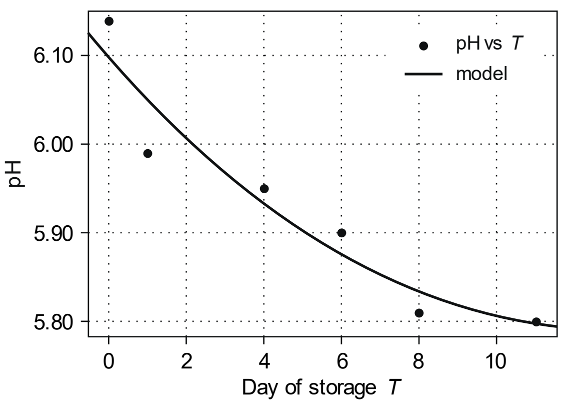

Fig. 3. Predictive model showing the relationship between pH and day of storage.

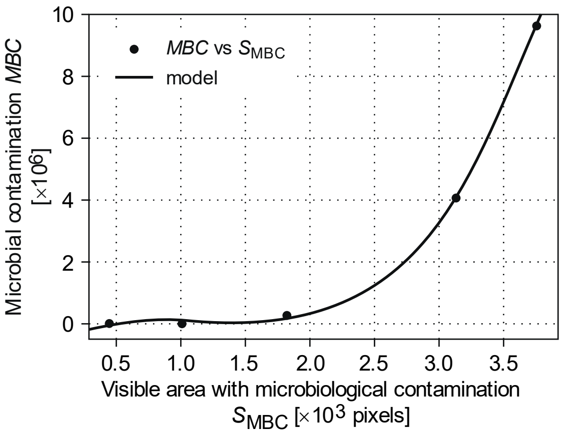

Fig. 4. Predictive model showing the relationship between the value describing microbiological contamination and the visible area with microbiological contamination on the surface of cheese.

Microbiological contamination is expressed as number of cells in the investigated sample (40 g).

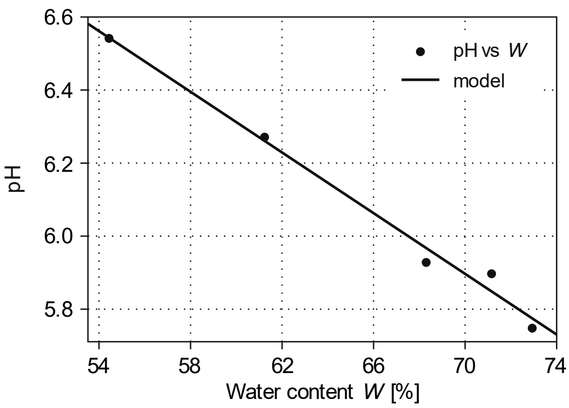

Fig. 5. Predictive model showing the relationship between pH and water water content in meat (easily measurable property).

$SE = 2.28 \times 10^{-14}$, and $PCC = 1.00$.

In addition to RPMs presented above, the following RPMs were developed: a model of the colour change of specific areas of cheese, presented by the HSV colour model, and model of appearance presented by the change of the area S_{MBC} of filamentous fungi. Examples of such models are given in our previous work [9].

Classification data using spectral characteristics after one day of storage

Examples of the determination of the classification data (number of the bands n, number of the band N, in which the minimum error is obtained in the investigated HSC. and the overlap error ε_{ov}) of two spectral classes in bacon using spectral data (visible spectrum) of different areas (spectral characteristics of meat tissue CL1 and fat tissue CL2) after one day of storage are shown in Fig. 6. These examples present results from converting the spectral characteristics into HSCs using Variant 2 of the procedure described in the subsection Method for hyperspectral analyses of the investigated areas.

Examples of determining n, N and ε_{ov} of spectral data in bacon after one day of storage are presented in Tab. 1. LDA and SVM-K classifiers were applied for separation of the spectral data classes.

Analysis of results obtained after one day of storage:

1. The values of n, N and ε_{ov} varied in a comparatively broad range in relation to the type of the investigated product, investigated area, classifier, and spectrum (visible or NIR), as well as from storage duration. The expectation that ε_{ov} will decrease when the number of intervals n increases was confirmed.
2. The value of ε_{ov} did not exceed a few tenths of a percent, which indicated small overlapping and high separability of the spectral data in different areas after one day of storage.
3. Better separability of the spectral classes was determined when the SVM-K classifier was used, in comparison with the results obtained using the LDA classifier.

Classification data using spectral characteristics between different days of storage

An example of the variation of ε_{ov} in relation to the number of the band of spectral data (NIR spectrum) between different days of storage for one object area (meat tissue in bacon) is shown in Fig. 7. An example of the determination of n, N and ε_{ov} of two spectral classes (visible spectrum) in bacon (meat tissue CL1 and fat tissue CL2) after 3 days of storage is presented in Fig. 8.

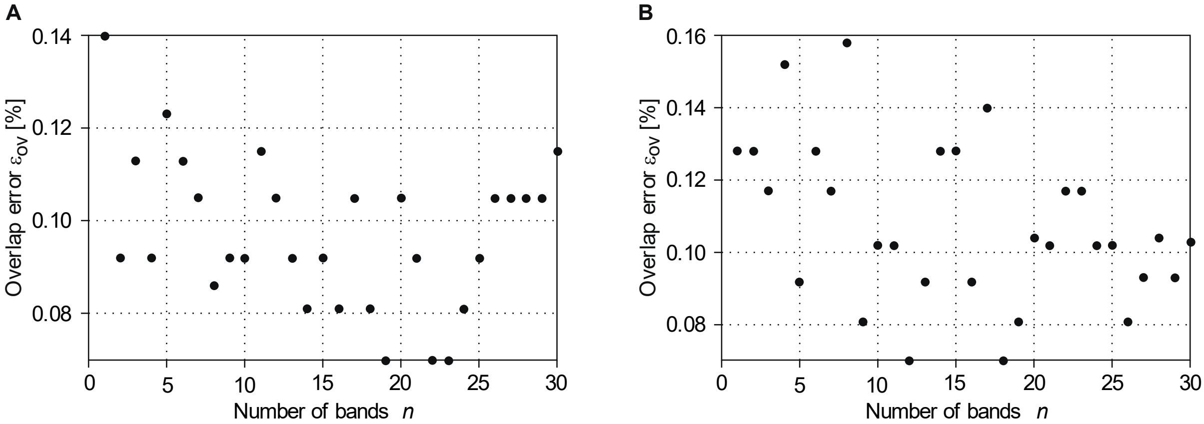

Fig. 6. Relation between the overlap error and the number of bands for bacon after one day of storage.

A – linear discriminant analysis classifier, B – kernel support vector machine classifier.
Spectral characteristics were obtained in visible spectrum. Spectral classes: CL1 – meat tissue, CL2 – fat tissue.

Tab. 1. Variation of the overlap error for bacon after one day of storage.

Day	Visible spectrum						Near-infrared spectrum					
	LDA classifier			SVM-K classifier			LDA classifier			SVM-K classifier		
	n	*N*	ε_{ov} [%]	*n*	*N*	ε_{ov} [%]	*n*	*N*	ε_{ov} [%]	*n*	*N*	ε_{ov} [%]
Variation between CL1 and CL2												
0	3	3	0.0–0.1	6	6	0.0–0.1	28	15	0.1–0.2	55	30	0.1–0.2
3	4	4	0.0–0.2	3	3	0.0–0.1	3	3	0.0–0.1	35	9	0.0–0.1
6	7	7	0.0–0.1	20	9	0.0–0.1	43	11	0.1–0.2	22	7	0.0–0.1
Variation between CL1 and CL3												
0	46	28	0.1–0.4	21	11	0.2–0.4	3	2	0.0–0.1	6	4	0.0–0.1
3	6	4	0.0–0.1	36	35	0.0–0.2	3	2	0.0–0.1	3	1	0.0–0.1
6	18	8	0.2–0.4	12	5	0.2–0.4	5	5	0.1–0.2	3	2	0.1–0.2
Variation between CL2 and CL3												
0	3	3	0.0–0.2	22	21	0.0–0.2	2	2	0.1–0.3	3	3	0.1–0.3
3	9	5	0.1–0.3	48	33	0.0–0.3	18	18	0.1–0.3	5	3	0.1–0.3
6	23	22	0.0–0.2	11	11	0.0–0.2	33	11	0.2–0.3	5	4	0.2–0.3

LDA – linear discriminant analysis, SVM-K – kernel support vector machine, *n* – number of bands, *N* – number of the band in which a minimum error was obtained, ε_{ov} – overlap error.
Spectral classes: CL1 – meat tissue, CL2 – fat tissue, CL3 – mixed tissue.

Examples of determining *n, N* and ε_{ov} of spectral data in bacon during storage are presented in Tab. 2. LDA and SVM-K classifiers were applied for separation of the spectral data classes.

Analysis of results obtained between different days of storage:

1. In frames of this investigation, the values of *n, N* and ε_{ov} vary in comparatively big range in the relation of the type of investigated product, investigated area, classifier, and spectrum (visible or NIR), as well as from a couple of days of storage.
2. The ε_{ov} don't exceed a few tenths of a percent, which indicates for small overlapping and high separability of the spectral data in one area in different days of storage.
3. It is determined better separability of the spectral classes when the SVM-K classifier is used in comparison with the results obtained using the LDA classifier.

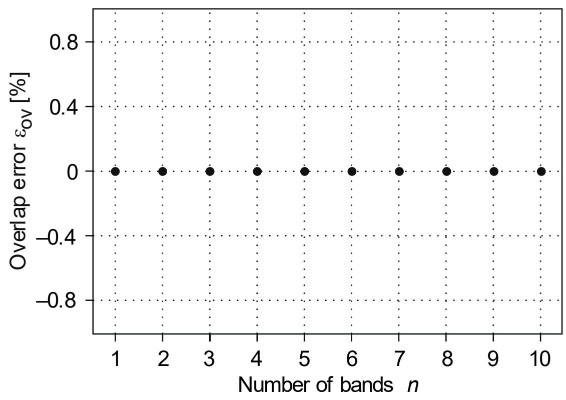

Fig. 7. Relation between the overlap error and the number of bands for bacon between day 5 and day 6 of storage.

Spectral characteristics were obtained in near-infrared spectrum. Spectral classes: CL1 – meat tissue.

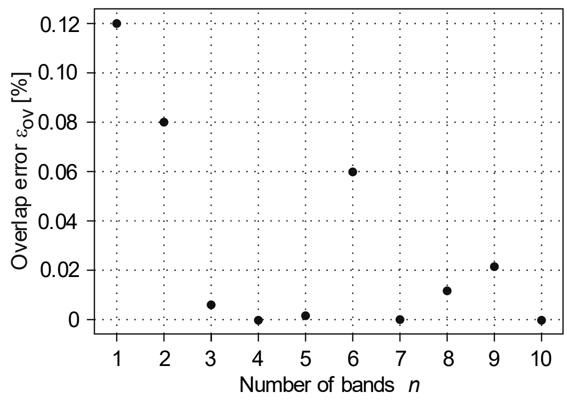

Fig. 8. Relation between the overlap error and the number of bands for bacon after 3 days of storage.

Spectral characteristics were obtained in visible spectrum. Spectral classes: CL1 – meat tissue, CL2 – fat tissue.

Tab. 2. Variation of the overlap error for bacon during a few days of storage.

Couple of days	Visible spectrum						Near-infrared spectrum					
	LDA classifier			SVM-K classifier			LDA classifier			SVM-K classifier		
	n	*N*	ε_{OV} [%]	*n*	*N*	ε_{OV} [%]	*n*	*N*	ε_{OV} [%]	*n*	*N*	ε_{OV} [%]
Variation in CL1												
0–1	2	1	0.0	2	1	0.0	35	1	0.2–0.4	67	4	0.2–0.3
0–2	2	1	0.0	2	1	0.0	36	1	0.2–0.4	39	1	0.2–0.4
0–3	2	1	0.0	2	2	0.0	43	30	0.3–0.4	42	14	0.3–0.4
0–4	2	1	0.0	2	2	0.0	34	27	0.2–0.4	90	20	0.3–0.4
1–2	5	1	0.1–0.3	4	1	0.1–0.3	36	1	0.3–0.4	92	59	0.3–0.4
3–4	20	17	0.3–0.5	14	4	0.3–0.5	50	42	0.3–0.5	9	5	0.2–0.4
Variation in CL2												
0–1	2	1	0.0	2	1	0.0	2	2	0.2–0.4	28	1	0.2–0.3
0–2	2	1	0.0	2	1	0.0	27	8	0.1–0.3	85	24	0.2–0.3
0–3	2	1	0.0	2	1	0.0	38	17	0.2–0.4	64	17	0.2–0.3
0–4	2	1	0.0	2	1	0.0	38	9	0.2–0.3	29	8	0.2–0.3
1–2	5	1	0.1–0.2	16	9	0.0–0.1	10	36	0.3–0.4	5	5	0.2–0.3
3–4	6	3	0.2–0.3	26	14	0.2–0.3	48	2	0.2–0.4	26	25	0.3–0.4
Variation in CL3												
0–1	2	1	0.0	2	1	0.0	21	21	0.2–0.3	45	31	0.2–0.3
0–2	2	1	0.0	2	1	0.0	22	8	0.0–0.1	28	14	0.1–0.2
0–3	2	1	0.0	2	1	0.0	30	10	0.1–0.2	38	11	0.1–0.2
0–4	2	1	0.0	2	1	0.0	25	14	0.0–0.2	14	4	0.1–0.2
1–2	17	5	0.0–0.2	18	5	0.0–0.1	18	5	0.1–0.3	11	4	0.1–0.3
3–4	64	20	0.2–0.4	9	4	0.1–0.3	30	24	0.2–0.4	63	30	0.2–0.3

LDA – linear discriminant analysis, SVM-K – kernel support vector machine, *n* – number of bands, *N* – number of the band in which a minimum error was obtained, ε_{OV} – overlap error.
Spectral classes: CL1 – meat tissue, CL2 – fat tissue, CL3 – mixed tissue.

Comparison of the separation accuracy between spectral data classes

A comparison of the separation accuracy between spectral data classes, when the spectral data is obtained from the overall measuring range of the spectrophotometer and from selected frequency bands of the HSC is presented below.

Tab. 3 gives the average value of the overlap error (ε_{ovav}) between spectral data classes in two different days T_i and T_j obtained in NIR spectral range.

Tab. 3. Average values of the overlap error for bacon on two different days of storage.

Couple of days	ε_{ovav} [%]			
	Whole spectrum		Selected frequency bands	
	CL1	CL2	CL1	CL2
1–2	24.2	8.4	0.3	0.3
2–3	5.7	2.1	0.3	0.3
3–4	4.5	2.3	0.3	0.4
4–5	0.0	0.0	0.0	0.0
5–6	0.0	0.0	0.0	0.0
1–3	1.1	1.1	0.1	0.0
3–5	0.0	0.0	0.0	0.0
5–7	0.0	0.0	0.0	0.0

Values were obtained in near-infrared spectral range.
ε_{ovav} – average value of the overlap error between spectral classes. Spectral classes: CL1 – meat tissue, CL2 – fat tissue.

The investigation of the class separability using empirical data, related to the predictive models, showed the following:

1. When processing spectral data in the NIR spectral region and in the whole measuring range of the spectrophotometer, the average overlap error reached a value of 24.2% for meat tissues and 8.4% for fat tissues.
2. When processing spectral data from selected frequency bands, the average overlap error reached a value of 0.3 % for meat tissues and 0.4 % for fat tissues.
3. There was a significant difference between the error values obtained based on the spectral data from the whole spectral range and values obtained using the spectral data from selected frequency bands. The difference in the classification accuracy was nearly two orders of magnitude.

DISCUSSION

The reason to investigate the changes of food products stored in these conditions (temperature 20 °C and lack of illumination) is the following. In many countries and regions, after various natural disasters, many small towns and villages remain without electricity for more than a week. This study aims to answer the question of what happened with the food products stored at homes, small restaurants or catering establishments in such cases.

Two additional limitations of applying the HSI technologies for the assessment of food freshness and safety were defined. These limitations were not discussed in previous studies in the field. They are related to the assessment of quality, freshness and safety of food products when the number of samples is limited because of the nature of the investigated products. The comparatively small number of samples or a small number of points in one spectral band of HSC, respectively, imposes additional limitations of the maximum number of bands, to which the spectral characteristics are divided.

A new simple MBA for evaluating freshness and safety of meat and dairy products was proposed. Freshness was represented by the duration of storage in specific conditions and safety was represented by the admissible time of storage. In contrast to traditional methods for assessment of food quality, freshness and safety, this approach can be used for rapid and non-destructive evaluation „on site“, i. e. in food shops, warehouses, catering services or homes. Freshness and safety were evaluated using three types of RPM. These models presented the changes in various specific features of the investigated food products during their storage.

In contrast to a traditional RPM, RPM1 presented the relationship between the value of X_{iPCA} of the measured feature X_i and the day of storage T_i.

A new simple method for HSA was proposed. Extraction and selection of food quality features were supported by this method. It was based on the spectral characteristics of the investigated food products obtained by traditional spectrophotometry. It converted spectral characteristics obtained in the whole measuring range of the spectrophotometer into HSC with a low number of bands.

This method avoids the basic disadvantages and restrictions of HIS technologies in the assessment of food quality and safety. It reduces sufficiently the number of bands in HSC in comparison with the traditional method used in HSI. The method uses a new criterion for bad selection. By using this method, the complex optical system for light dispersion in the hyperspectral sensor can be replaced with an optical system of a traditional spectrophotometer.

A comparison of the separation accuracy between spectral data classes, when the spectral data were obtained from the whole measuring range of the spectrophotometer and from the selected frequency band of the HSCs, was carried out.

The results from the investigation showed that the assessment of freshness and safety based on spectral data from a selected frequency band significantly improved the classification accuracy in comparison with the variant when the data were extracted from spectral characteristics from the whole measuring range of the spectrophotometer. The overlap error ε_{ov} between spectral classes was by approximately two orders of magnitude lower when using data from the selected frequency band.

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