Methods and tools for sensors information processing

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Abstract: Current trends in the analysis of food products are related to contactless and hygienic measurements. Adapted, researched and used in this study are hardware and software tools for complex, express, automated evaluation of basic properties and categorization of food products, including: color measurement, spectral analysis and software modules for research, analysis and categorization of foodstuffs including visual image analysis tools, spectral and hyperspectral characteristics, and categorization tools. For that purpose, methods for selecting informative wavelengths for hyperspectral analysis are discussed. Classifiers as Discriminant analysis and SVM are used for classification of food products. Combining visual image data, spectral and hyperspectral analysis is also a method of improving classification accuracy. The results obtained are suitable for the implementation of current trends in the analysis of food related to contactless and hygienic measurements.

Key-words: Spectral analysis, image processing, hyperspectral data, discriminant analysis, classification

1 Introduction

The hygienic measurement of food products is one of the important issues underlying the Hazard Analysis and Critical Control Point (HACCP) system. Non-contact methods are a suitable alternative to traditional methods of measuring the parameters of these products at different stages of their production. This is also mentioned in [1,7,9]. In addition, most of the methods for assessing the quality and condition of the product include laboratory analyzes requiring breakdown of the measured sample and/or time-consuming and laborintensive requiring highly qualified staff. The education in this scientific field also need developing and research stages [8].

During storage, there are various changes in food that inevitably affect their composition and properties, nutritional value and hence quality. The nature and extent of these changes depend on the conditions and duration of storage as well as on the condition of the product. In most cases, these changes are undesirable as they lead to a decrease in the quality of food products. Hence the requirement that storage conditions should be selected so as to exclude or at least minimize unwanted changes. Changes in storage may be due to different processes – physical, chemical, physiological, autolysis, microbiological. In-depth knowledge of these changes is a prerequisite for the proper organization of the storage of food products. Image acquisition, processing and analysis systems can be deployed at different stages of food production and storage. Also the problem with appropriate algorithms for analysis of food products [3]. In these cases, video cameras are convenient for use in hazardous environments, where the operator is struggling to monitor the process. The speed of getting images in some video cameras is much higher than that of human vision and they are suitable for tracking and managing fast-changing processes.

Visible (VIS) and Near Infrared (NIRS) spectroscopy is a technology primarily used to determine changes in food products composition and to assess its quality. Major applications of spectrophotometric methods in food analysis can be the determination of sensory properties, determination of composition, moisture content, aging and alteration of its storage characteristics.

Hyper-spectral analysis systems find applications in solving tasks related to food quality assessment, also for agriculture products [2]. This method determines the moisture content and distribution of the materials as salt, sugar, the identification of the composition, the presence of impurities. The main advantage of the hyperspectral analysis over the other two image analysis and spectral analysis methods is that a full spectrum is obtained for each scanned point of the object and no pre-knowledge of the sample is required, and complete information on the object is obtained upon further processing. Also, spatial information about the object is obtained, allowing for more accurate segmentation and classification of the image.

An experience of using methods mentioned above is described. These optical methods are used for nondestructive analysis of meat and meat products, dairy products, bread and bakery products. A comparative analysis is made of methods for selecting informative color features, reducing the amount of data from spectral characteristics. Methods for selecting informative wavelengths for hyperspectral analysis are discussed. Four classifiers are used Naïve Bayes, kNN, Discriminant analysis and SVM for classification of food products during storage. Mathematical models are expressed that can be used to predict the storage period of food products with sufficient accuracy.

2 Material and methods

The obtaining of spectral characteristics was done by converting LMS model values into reflectance spectra in the VIS range, in the range 390-730nm, by mathematical dependencies where conversion is possible in both directions of equality [4]. The conversion functions applied are 10° observer (Stiles and Burch 10°, RGB (1959)) and illumination D65 (average daylight with UV component (6500K)).

Hyperspectral images were obtained through a point-scan system developed by the Automation and Mechatronics Department of Ruse University, A. Kanchev, Bulgaria [5]. The point size is 5x5mm. The overall image size is 90x50mm. The measurements are in two spectral regions VIS and NIR.

Latent variables (LV) obtained by partial least squares regression (PLSR) [6]. PLS (Partial leastsquares) regression is a technique used for data that contains correlated predictive variables. This technique constructs new predictive variables known as components as a linear combination of the original predictive values. PLS constructs these components by assuming the observed values, resulting in a more accurate model with better forecasting.

In the principal components analysis (PCA) [10], the extraction of characteristic properties is a transformation of the original data with all of its variables into a sample of reduced ones. All measurements or variables that are designed in a small size area are used. The principal component analysis (PCA) creates an orthogonal coordinate system where the axes are arranged according to the dispersion in the original data to which the corresponding major component and the dispersions and the principal values are related.

The discriminant function analysis (DA) [5] used is a multidimensional data analysis that is applied when there is a need to "predict" the values of a clustering variable. This is also called classification or image recognition. Linear discriminant analysis constructs linear discriminative functions from predictors. The goal is to obtain a rule for assigning a new observation to a class. Assigning or "allocating" to a certain class of characteristics is also necessary for the present development.

3 Results and discussion

Examples of image analysis, spectral and hyperspectral characteristics of basic foods are offered. Image analysis is demonstrated by color features classification. The spectral characteristics were used to detect contaminated agricultural products. Hyperspectral analysis was applied to meat products.

Figure 1a) shows an example of the separation of control sample and yogurt with 0.4% dried and ground bee pollen, and Figure 1b) of the control and yogurt with the addition of 0.8% dried and ground bee pollen in both cases a discriminant classifier with a quadratic separating function was used. The figure shows that in both cases the total classification error is up to 10%.

The results for all the cases considered in this paper for classification between the tested samples with discriminant analysis using nonlinear separation functions are summarized.

The results show that there is a better separation between control and yoghurts with the addition of dried and ground bee pollen, whereas in extracts with samples such separation by color components is difficult to achieve since the overall classification error in this case is over 20%.



Figure 1. Classification of yoghurt with addition of bee pollen with discriminant analysis

16 color The informativeness of features, representing the mean values of the color components of 5 color models (RGB, HSV, Lab, LCH, CMYK) with respect to object areas of milk with added bee pollen, was evaluated. From the analysis of the results, it was found that the color components R (RGB), G (RGB), B (RGB), L (Lab), M (CMYK), Y (suitable for the separation of yoghurt with the addition of bee pollen) CMYK), Y (CMYK). A better separation was found between the control sample and those with ground pollen than with the extract samples.

Informative wavelength ranges were selected using a first derivative. Results for the reduction of spectral characteristics data by latent variables and principal components are presented.

Figure 2 presents examples of the obtained spectral characteristics of healthy and contaminated grapes of different varieties. Variety 3 shows a clear separation between healthy and infected grapes. When presenting two varieties - 2 and 3, it can also be seen that they can be separated by their spectral characteristics.



Figure 2. Spectral characteristics of grapes

The selection of informative wavelengths is made by the first derivative of the spectral characteristics. Figure 3 presents the spectral characteristics of all healthy and infected varieties and their first derivative. Spectral characteristics overlap between healthy and infected varieties and between them. When using the first derivative, ranges of change in the nature of the spectral characteristics are clearly distinguished. They are defined by the intersection of the zero axis of the first derivative.



Figure 3. Determination of the spectral characteristics ranges by the first derivative

Table 1 lists the spectral characteristics determined by the first derivative of the four bands (d1-d4). In addition, the full spectrum (d5) from 380nm to 780nm was used in the work.

Table 1. Ranges of variation of spectral characteristics

Name	d1	d2	d3	d4	d5		
Range,	380-	460-	520-	660-	380-		
nm	460	520	660	780	780		

The reduction of spectral characteristics data is done by presenting them with latent variables and principal components. It has been found that 2 latent variables and two principal components are required to describe the spectral characteristics. The use of a larger number of these coefficients does not change the results obtained. Figure 4 shows graphs of latent variable spectral characteristics reduced, using their full spectrum. There is a clear distinction between the latent variables for healthy and infected varieties and between them.



Figure 4. Presentation of grape varieties by latent variables of spectral characteristics

Table 2 lists the results of classification by latent variables and principal components of the spectral characteristics. Like the direct use of spectral characteristics, the latent variables exhibit the same nature of resolution. In these variables, separation is impossible (> 20%) between healthy and infected for varieties 1 and 2, and between the two varieties. Latency variable resolution is possible for variety 3,

both between infected and healthy for this variety, and between 1-3, 2-3 varieties.

When using the main components of the spectral characteristics, it is possible for the varieties to be separated both contaminated and healthy and between them with a total classification error of 1-2%.

	s1z-s1b		s2z-s2b		s3z-s3b		s1z-s2z		s1z-s3z			s2z-s3z						
	Q	DQ	Mah	Q	DQ	Mah	Q	DQ	Mah	Q	DQ	Mah	Q	DQ	Mah	Q	DQ	Mah
LV	31%	31%	33%	45%	45%	45%	1%	1%	1%	45%	45%	45%	1%	1%	1%	1%	1%	1%
PC	2%	1%	1%	2%	1%	1%	1%	2%	1%	2%	1%	1%	2%	1%	1%	2%	1%	1%
s1-s3 - grape varieties; z - healthy; b - diseased; Q - quadratic separation function; DQ - diagonal-quadratic separation																		
function; Mah - Mahalanobis separation function; LV - latent variables; PC - principal components																		

Table 2. Separability between healthy and diseased grapes by latent variables and principal components of spectral characteristics by discriminant analysis

After identifying the optimal wavelengths, the spectral data were reduced to 10 for meat and 12 wavelengths for sausage. The reduced spectral data were analyzed by principal component analysis. PCAs look for linear combinations of variables describing the data without considering the defined classes.

The graphs for the first two components describing over 95% of the variance of the meat and sausage

data are presented in Figure 5, showing that the four meat classes and the three sausage classes together with the background in the hyperspectral image can be separated into separate classes. The four meat groups, and the three sausage groups, indicate that objects in a particular class have similar values that differentiate them from other classes (or clusters). For meat, the classes are very close to each other.



Figure 5. Transform spectral data through the first two principal components

The results of the principal component analysis obtained from the spectral data can be extracted in the form of an image by presenting the class to which these data are and returning to their spatial position and visualizing them. The two-dimensional matrix representing the reflections at each point as columns is multiplied by the weight vector obtained by PCA. It can be seen from Figure 6 that the method used results in a contrast between the different cross-sectional areas of the hyperspectral cube at the spectral wavelength specified as an informative wavelength.



Figure 6. Visualization of hyperspectral data

The results of the acquisition, processing and analysis of hyperspectral information show that, by using hyperspectral images in the visible and near infrared and method of principal component analysis, informative signs can be extracted and used to determine the freshness of pork and sausages. The optimum wavelengths are determined by the spectral characteristics using a second reflection derivative.

The possibility of separating areas of fat, meat, bone and transitional areas into hyperspectral images was investigated, with the aim of defining such spectral ranges in which the individual areas of fat, meat, bone can be identified.

A study has been conducted to identify object zones

in hyperspectral images. For each point in the image, reflection and PCA analysis data were used. On the basis of the visual image, a standard was created containing the object areas with meat, fat and transition area for sausages and meat, fat, bone tissue and transition areas for cutlets (Figure 7). In addition, an area for the background is presented, but it is excluded from the data analysis because the background is removed and not considered in the study. The choice of which class a particular pixel belongs to is made, such as in sausages, if over 50% of the area in the pixel is meat, then the pixels are assigned to the meat class as well as to the other pixels in the image.



a) original image



1-fat; 2-meat; 3 transitional areas; 4-background

Figure 7. Image of sausage with defined object areas

The results of the analysis of the spectral data obtained can be transformed in such a way that the object area from the scanned object can be recognized or to determine on which day of storage the data are received. The first two components of the spectral data obtained describe more than 95% of the variance in these data. Pseudo-color images were obtained by multiplying the weights from the PCA analysis for the selected spectral ranges by the spectral data in those ranges. The pixels in these pseudo-color images have the same properties as the original features. These images show areas of the same color, or in other words, with the same values of weight coefficients. In this way, a comparison can be made with the created standard by checking that the pixels in the particular predetermined area have the same values of the weight coefficients, and then whether there is a difference between the values in the different areas of the image represented in the pseudo color.

Combining visual image data, spectral and hyperspectral analysis is also a method of improving classification accuracy [2,6,10].

4 Conclusion

An analysis has been made and the existing methods and technical means for non-destructive evaluation of the quality of food products have been systematized. From the analysis it was found that the methods for analysis of images, spectral and hyperspectral characteristics of the products are objective for evaluating the main quality indicators of the mentioned products.

The results of the study on the separability of data by day within a given class indicate that better results are obtained in studies based on spectral data in the visible range. This is an expected result since the major part of the investigated properties related to food quality are visible properties that can be analyzed in the visible spectrum of reflected light.

Software tools have been adapted to implement the proposed procedures for digital image analysis, spectral and hyperspectral characteristics for the purpose of character extraction and classification.

Adapted, researched and used in this study are hardware and software tools for complex, express, automated evaluation of basic properties and categorization of food products, including: color measurement, spectral analysis and software modules for research, analysis and categorization of foodstuffs including visual image analysis tools, spectral and hyperspectral characteristics, and categorization tools.

The proposed methods and tools are suitable for the implementation of current trends in the analysis of food related to contactless and hygienic measurements.

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