

INTECHN PLATFORM FOR GRAIN SAMPLE QUALITY ASSESSMENT

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Abstract

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This paper presents the approaches, methods and tools for assessment of main quality features of grain samples using spectra analysis of the sample elements. They are developed within the frames of the research project "Development of Intelligent Technologies for Assessment of Quality and Safety of Food Agricultural Products", founded by the Bulgarian National Science Fund. The sample elements are divided in nine quality groups according to their surface features, which are related to the color characteristics and surface texture. Three different approaches are used for feature extraction from spectra and for data dimensionality reduction: principal component analysis and combinations of two kinds of wavelet analyses and principal component analysis. Three classifiers, based on radial basis elements, are used for object classification in the quality groups. The validation, training and testing errors of the classification procedures are evaluated. The results obtained are compared with the results obtained by the Unscrambler referent platform.

Key words: grain sample quality assessment, feature extraction, spectra analysis, classification

Abbreviations: INTECHN - Abbreviation of the research project; NIR - Near infrared reflectance; LDA - Linear Discriminant Analysis; SVM - Support Vector Machines; SIMCA - Soft Independent Modeling of Class Analogy (SIMCA); PCA - Principal Component Analysis

Introduction

The food product quality and safety assessment is a very important problem. It is main goal of different research programs. The higher EU requirements about food quality and safety require new, objective technologies for assessment of food product quality and safety to be developed. This was the main goal of the INTECHN project (Development of Intelligent Technologies for Assessment of Quality and Safety of Food Agricultural

Products), founded by the Bulgarian National Science Fund. Express objective, intelligent methods and tools for assessment of main quality and safety features of different food products, like cereals, fruits, vegetables, milk, dairy products, meat, meat products and eggs were developed and investigated within the frames of the project.

Two different approaches are used to obtain a complex assessment of main quality features of the investigated product. The first approach is based on the analysis of the object color images.

It is expected visible features, related to the object color, shape and dimensions to be obtained as a result of this analysis. The second approach is based on the analysis of the object spectra. It can give information about object features, which cannot be extracted from the images.

The approaches, methods and tools for assessment of main quality features of the grain samples are presented in the paper. They are based on the spectra analysis of the sample elements using reflectance spectroscopy. In spite of they are illustrated for maize grain samples, they are used for quality assessment of other kinds of food products.

According to Bulgarian Government Standard the main quality features of maize grains are: inherent for the variety appearance, shape, color, smell, taste, moisture content and impurities. As normal grains are considered the hole grains and the broken grains (bigger then the half of the hole grain), which have inherent for the variety appearance, shape and color. The grain impurities include broken grains (smaller then the half of the hole grain), heat-damaged grains, small grains, shriveled grains, green grains, sprouted grains, mould grains, smutty grains, infected (with *Fusarium*) grains. The non grain impurities include corn-cob particles, leaf and stem fractions, pebbles, soil, sand, metal particles as well as harmful elements (bunt).

Grain visible features, related to the object surface color and texture characteristics are evaluated in this study. The grain sample elements are distributed in the following main quality groups: grains whit inherent for the variety color, heat-damaged grains, green grains, mould grains, smutty grains, infected (with *Fusarium*) grains, sprouted grains and non grain impurities.

The grain sample characteristics presented above have visible symptoms on the grain surface. They are related to the specific grain appearance, surface color and surface texture and they are assessed by an expert on the basis of visual estimation only. This method for assessment presumes a

computer vision system to be used for evaluation of a big part of these quality features (Brosnan and Sun, 2003; Liu and Paulsen, 2000; Luo et al., 1999; Mladenov et al., 2011). There are many materials published, in which color characteristics analysis is used to assess some particular quality features like authenticity (Liu and Paulsen, 2000; Majumdar and Jayas, 2000a), variety (Paliwal et al., 2003a; Paliwal et al., 2003b), infections (Ning et al., 1988; Mladenov et al., 2011), germination (Mladenov and Dejanov, 2008), etc. Morphological features, related to the grain shape and geometrical parameters are used for assessment of variety (Majumdar and Jayas, 2000b), purity (Paliwal et al., 2001; Mladenov et al., 2004), different injuries (Schneider and Kutzbach, 1999) and other similar grain properties.

Some preliminary investigations (Mladenov et al., 2011) showed that the analysis of object color images could not give sufficiently precise assessment of some grain sample elements, like infected grains, mould grains and non grain impurities. This was determined by the fact that in comparison with the normal grains, not only color features of such objects are changed, but the surface texture are changed too. It was difficult to detect this change using a computer vision system.

Visible (VIS) and near infrared (NIR) spectra analyses are applied in the assessment of different grain quality features (Huang et al., 2008). They are mainly used in tasks, related to the determination of qualitative and quantitative features, like grain composition, dry matter content, moisture content, starch, protein, glutenin, vitamins, toxins, minerals content, as well as to the detection of grain infections. Different maize starch yield calibration models are developed for predicting maize starch content (Paulsen et al., 2003; Paulsen and Singh, 2004). Baye et al. (2006) use single-kernel near infrared spectroscopy (NIRS) to accurately predict the internal kernel composition. Dowell et al. (2006) use NIRS analysis for predicting protein content, moisture content and flour color b^* values. Wesley et al. (2001) develop a method

for predicting the protein composition using NIR spectroscopy. Miralbés (2003) analyses wet gluten, dry gluten, moisture, protein, and alveograph parameters (W, P, and P/L) of whole wheat using NIR transmittance spectroscopy. Modified partial least squares models on NIR spectra (850–1048.2 nm) are developed for each constituent or physical property. The best models are obtained for protein, moisture, wet gluten, and dry gluten with $r^2 = 0.99$, 0.99, 0.95, and 0.96, respectively.

The spectra analysis is used for the detection of different grain infections. Determination and prediction of the content of ergosterols and different kind of mycotoxins like aflatoxin, fumonisin and other mycotoxins is very important task, because mycotoxins are toxic for animals and humans. Dowell et al. (2002), use reflectance and transmittance VIS and NIR spectroscopy to detect fumonisin in single corn kernels infected with *Fusarium verticillioides*. They classify accurately corn kernels as fumonisin positive or negative, respectively. A method for determination of *Fusarium graminearum* infection is proposed in Kos et al. (2003). The ergosterol and the toxin deoxynivalenol in corn kernels could be determined using this method. The classification accuracy is up to 100% for individual samples. Pearson et al. (2001) evaluates transmittance spectra (500 to 950 nm) and reflectance spectra (550 to 1700 nm) as tools for aflatoxin determination in single whole corn kernels. They use discriminant analysis and partial least squares regression for spectral data processing. The best results are obtained using two feature discriminant analyses of the transmittance data. Peiris et al. (2010), propose a NIRS method for estimation of sound kernels and *Fusarium*-damaged kernels proportions in grain and for estimation of deoxynivalenol levels. The method classifies sound and *Fusarium* damaged kernels with an accuracy of 98.8 and 99.9%, respectively. Ruan et al. (2002), develop a neural network based method for deoxynivalenol levels assessment in barley using NIRS from 400 to 2400 nm. They analyze NIR spectra of barley

samples with different deoxynivalenol levels from 0.3 to 50.8 ppm. Girolamo et al. (2009), use Fourier transforms NIRS for rapid and non-invasive analysis of deoxynivalenol in durum and common wheat. A qualitative model for discrimination of blank and naturally contaminated wheat samples is developed. Classification accuracy of the model is 69% of the 65 validation samples.

NIR spectroscopy is applied for assessment of grain moisture level too. Mahesh et al. (2010), present a new method using NIR hyperspectral imaging system (960–1700 nm) to identify five western Canadian wheat classes at different moisture levels. The authors find that the linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) can classify moisture contents with classification accuracies of 89–91 and 91–99%, respectively, independent of wheat classes. Once wheat classes are identified, classification accuracies of 90–100 and 72–99% are observed using LDA and QDA respectively, when identifying specific moisture levels.

As it is seen in the references cited above, different methods like Principal Component Regression, Partial Least Squares Regression, Principal Component Analysis, Hierarchical Cluster Analysis and other methods are used for developing a model to predict a property of interest, as well as for feature extraction and large and complex data reduction. Methods like K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), Cluster Analysis, Support Vector Machines (SVM), Neural Networks (NN) and Soft Independent Modeling of Class Analogy (SIMCA) are used for the assessment of different grain features using data from the grain spectra.

The goal of the paper is to present the INTECHN platform approaches, methods and tools for assessment of main quality features of the grain samples using reflectance spectroscopy. In contrast to the investigations presented above, which are related to the grain composition assessment, grain characteristics, which have visible symptoms on the grain surface, are analyzed in this study. A

part of the results of maize grain sample element classification is presented too. The results obtained are compared with the results obtained by the Unscrambler referent platform.

Materials and Methods

INTECHN platform structure

The INTECHN platform includes the following main modules: module for assessment of quality properties of cereals, module for assessment of quality properties of fruits and vegetables, module for assessment of quality properties and safety of milk and dairy products, module for assessment of quality properties and safety of meat and meat products; module for assessment of quality properties and safety of eggs. Each of the INTECHN platform modules has relatively independent structure, functions and tools, because of the specificity of the technologies for quality assessment of different products. The modules are implemented and integrated in MATLAB environment.

The INTECHN platform structure is organized in three levels (Figure 1):

Information source level. This level includes information resources for assessment of main quality and safety properties of the investigated objects. Computer vision system, spectrophotometers and specialized sensors like moisture meter, conductivity meter, pH meter are used as a main information sources. This level also includes other external information resources like standards, normative requirements, information systems and other sources related to the subject area.

Software module level. This level includes software tools for preliminarily processing and analysis of input information and for classification of the investigated objects into the quality groups defined. Some existing software platforms, like MATLAB, Pirouette и Unscrambler, as well as original software tools are used for food product quality assessment. Appropriate graphical user interface is developed for each of the modules.

User level. This level includes appropriate soft-

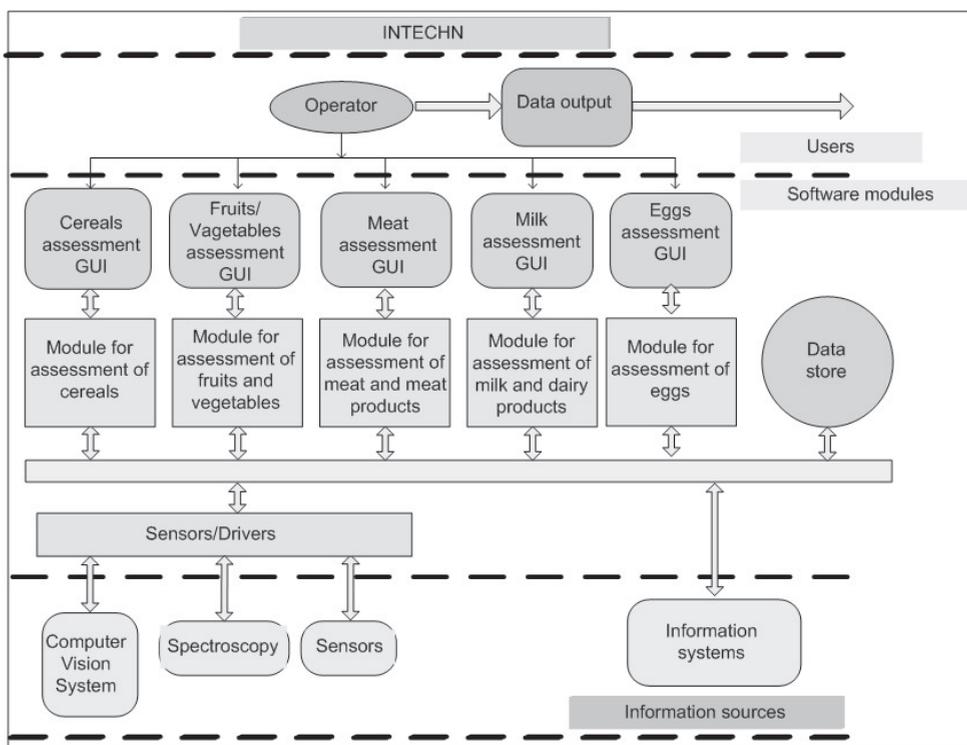


Fig. 1. INTECHN platform structure

ware tools for presenting the results from analysis and object quality assessment.

INTECHN platform hardware

The main INTECHN platform hardware

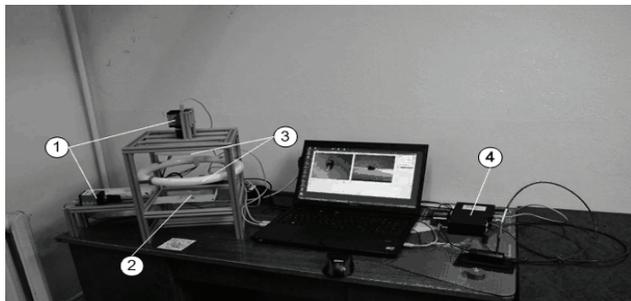


Fig. 2. INTECHN platform hardware components

components (Figure 2) are the computer vision system (CVS) and spectrophotometer (4) (QE65000, Ocean Optics, USA). The INTECHN platform CVS includes two color CCD cameras (3) (DFK31AU03, The IMAGINGSOURCE, Germany) (1) with lenses (PENTAX B2514D, Hoya Corporation, Japan), which gave a possibility to form color images of the investigated object (2) in two planes (horizontal and vertical). The illumination system includes two luminescent ring-shaped units (3), which have different diameters. It is used for direct object illumination. A portable computer model Dell Vostro 1720 is used for implementation of the INTECHN platform software procedures.

Classification of the grain sample elements

Grain sample classification groups

In conformity with their surface characteristics the grain sample elements are distributed in the groups (classes) and sub groups (subclasses) presented in Table 1.

Maize grain samples of the Kneja-433 variety are used in the investigation. The Maize Research Institute-Kneja, Bulgaria, produces this variety. The samples were gathered in one corn-growing season of one crop year and from one growing location. Principally, the INTECHN platform presumes the grain kind, variety and hybrid to

be specified when we develop a new data base. There is a possibility for the growing location to be specified too.

Features extraction from spectra

The spectral characteristics of grain sample elements were obtained using QE65000 (Ocean Optics, USA) spectrophotometer. Each characteristic is a vector with about 1500 components. Principle Component Analysis and combination of Wavelet descriptions and PCA are used for extracting typical features from object spectra and for input data reduction. The following Wavelet coefficients are used: Wavelet1- detail coefficients and Wavelet2- approximation coefficients. The operator can select one of the following wavelet functions: Haar, Daubechies2, Coiflet2 and Symlet2. The level of decomposition can vary from $m=1$ to $m=4$. The most informative wavelet coefficients are chosen using the PCA method.

Table 1

Maize grain sample classes and subclasses

Classes	Class features
1cc	Grains whit inherent for the variety color, back side
2cc	Grains whit inherent for the variety color, germ side
3cc	Heat-damaged grains
4cc	Green grains
5cc	Mouldy grains
6cc	Bunt, smutty grains
7cc	Infected (with Fusarium) grains
8cc	Sprouted grains
9cc	Non grain impurities
9cc1	Corn-cob particles
9cc2	Leaf fractions
9cc3	Stem fractions
9cc4	Pebbles
9cc5	Soil
9cc6	Sand

Development of grain sample group models

The sets of descriptions extracted from grain sample training sets are used for developing the models of the grain sample quality groups. Each class model is presented by the class center (the average value of the class training data) and the class boundary surface. The boundary surface is determined through a threshold value of the covariance of the class training data. It is relevant to remark that models are created only for the first eight groups. A correct model for the 9-th grain group cannot be created because of the fact that the spectral characteristics of elements of this class could be sufficiently different in each subsequent grain sample.

The task for grain sample class modeling is reduced to a task for approximation of the grain class areas. For this purpose, classifiers based on Radial Basis Elements (RBEs) are used. Classifiers, based on RBEs (Howlett and Jain, 2001; Huang and Zhao, 2005) are used in terms of the simplicity of the classification procedure and the accuracy of the class area approximation. Furthermore, if we set an appropriate value of the RBE bias and a minimal threshold Δ of its output, it becomes clear what part of input objects will be included within the class boundary and it is easy to change the dimensions of the particular class area.

Classifiers for class modeling

The following neural classifiers, based on RBEs (Mladenov et al., 2011), are used for class model development.

Classifier 1 (CSRBE). Only one RBE is used for approximation of each class area (Figure 3). The RBEs centers correspond to class average values obtained from class training sets.

The following denotations are used: f_{oi} is the output of i -th RBE, which corresponds to class ω_i ; Δ is threshold value, which limits class area dimensions.

In the case, when one standard RBE is used for each class area approximation, the class boundaries are round shaped. This corresponds to the case,

when the input vectors components distributions are equal in all directions of feature space. If this precondition is not carried out, then the class area shape can be sufficiently different from sphere

The bias value of the i -th RBE is determined by the equation:

$$bi = 0.833/(k \cdot \sigma_{oi}), \quad (1)$$

where σ_{oi} is a standard deviation of vectors of class ω_i ; k is a parameter, which determines the dimension of class boundary surface.

Classifier 2 (CDRBE). Another decision for class areas approximation gives the classifier architecture (CDRBE), presented in Figure 4.

The first classifier layer consists of m transforming elements, which recalculate input vectors coordinates in the local coordinate systems, whose axes coincide with class axes of inertia.

The next layer consists of $n \times m$ RBEs, which are distributed in m sub layers (m is the number of classes). The number of RBEs in each sub layer is equal to n (n is the input vector dimensionality). Each RBE has one input, connected with one of the input vector coordinates. The RBEs centers coincide with the average values of the projections of training set vectors onto the corresponding coordinates of the class local coordinate system. The RBEs biases are set in correspondence with the standard deviations of the respective input vector coordinate projections ($\sigma_{x1oi}, \sigma_{x2oi}, \dots, \sigma_{xnnoi}$).

The third layer consists of m RBEs. The weights of all RBEs are equal (1, 1... 1). The RBEs outputs are the weighted distances of the input vector to the centers of non – spherical classes. To determine to what class the input vector belongs, the output f_{oi} with maximum value is chosen. This value has to exceed the threshold value Δ of the threshold element (the last element of the classifier architecture).

The classifier architecture presented above gives a possibility to form classes, whose dimensions along the directions of the separate coordinate axes are different. Changing the RBEs biases and the

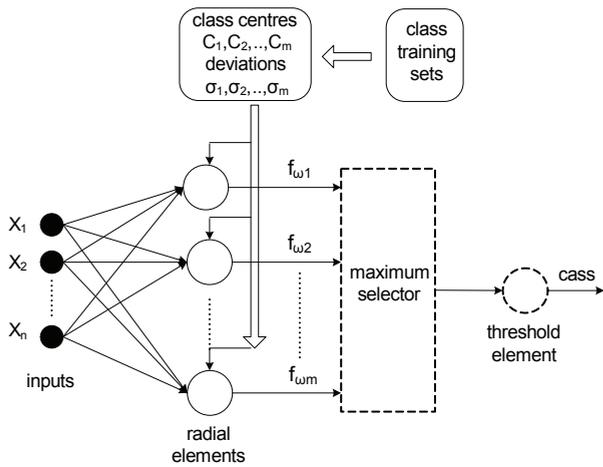


Fig. 3. Round shaped class areas approximation using standard RBEs (CSRBE)

threshold value Δ we can vary the class shape from a sphere to shape close to a parallelepiped.

Classifier 3 (CRBEP). The third classifier based on RBEs (CRBEP) is presented in Figure 5. It is intended for classification in overlapping classes, as the areas of some classes are expected to be so. The classifier approximates the class areas using standard (or decomposing) RBEs and the accumulated during classification number of vectors of each of the classes is interpreted as class potential V_{oi} . This potential can be defined as:

$$V_{oi} = N_i / N_{max} \quad (2)$$

where N_i is the number of vectors, which are currently classified in class ω_i ; N_{max} is the number of vectors, which are currently classified in the class with maximum classifications.

As it is shown in Figure 5, the class potential V_{oi} introduces an additional correction $\Delta f_{oi} = k_v \cdot V_{oi} / D(X, C_i)$ (k_v is a weight coefficient, $D(X, C_i)$ is Euclidean distance between the input vector X and the i -th class center) of the assessment f_{oi} , formed by the i -th RBE. This correction displaces the probability density function f_{oi} with a value, which is proportional to the current number of vectors of the class ω_i .

The effect of the correction comes down to a

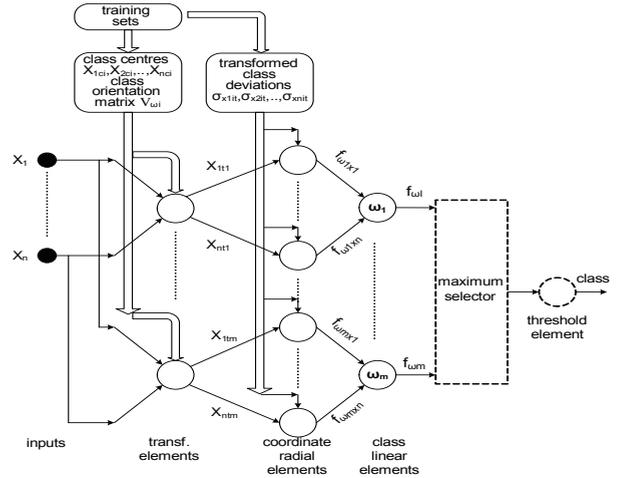


Fig. 4. Classifier with decomposing RBEs (CDRBE)

displacement of the boundary between the overlapping class areas. The displacement depends on the ratio of accumulated number of vectors in each of the classes.

Classifier validation

The classifiers presented in section 2.3.4 are trained and validated using a specific cross-validation procedure. The goal of the validation is to select appropriate data model description, appropriate classifier and to obtain the optimal classifier parameters k and k_v .

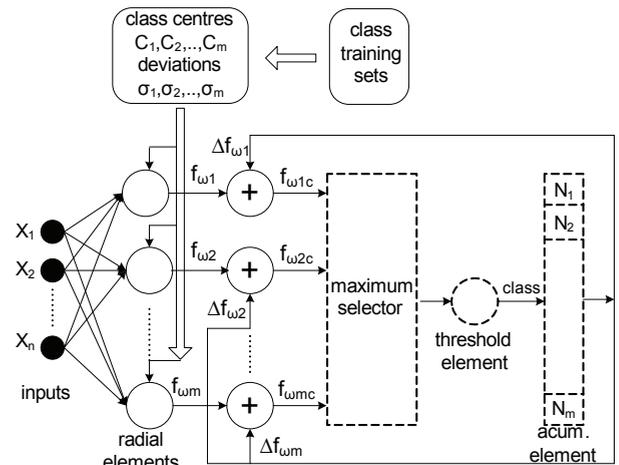


Fig. 5. Classifier architecture (CRBEP), which takes into consideration the classes potentials

In comparison with the standard cross-validation approach (K fold cross-validation), the INTECHN platform validation is based on the following procedure. In spite of the classifiers create models of the first eight grain sample groups, some elements of the 9cc group are used in classifier validation. This led to the limitation of the class area dimensions, which was a precondition a big part of non-grain impurities to be rejected from the classifier. In that case this result is a correct classification.

Association of Unknown Objects with One of the Models Defined

As it was mention above, a correct model for the 9-th grain group could not be created. A part of the descriptions of such objects can get into the boundaries of the eight classes defined. A big part of them will get outside the class areas and can be located in a random place in the feature space. These descriptions can be considered as noisy vectors. It can be assumed that the comparatively compact class areas of the objects from the first eight groups are submerged in a noisy environment. Therefore, the task for grain sample element categorization can be interpreted as a task for classification in classes, whose boundaries have definite shapes, dimensions and location in the feature space, and they are situated in a noisy environment.

Under this formulation the use of popular strategies like Discriminant analysis, Cluster analysis, Support Vector Machines, K-Nearest Neighbours and some other methods, which build boundaries between class areas, is obviously not a good choice. This is due to the fact that for the class 9cc, which correspond with the 9-th grain group, a correct model cannot be created. If a model of this class is developed using elements from the training set of the non grain impurities, it can be expected, that a big part of elements from the testing set of this group will get outside the class 9cc model and will get into other class areas. Thus, this will be an incorrect classification.

In conformity with this formulation, models of the 1cc, 2cc, ..., 8cc classes, corresponding to the first eight grain groups, are created using object descriptions from the respective training sets. The description of each unknown object is used as a classifier input. The output f_{oi} with the maximum value is selected. If this value exceeds the threshold Δ , the unknown object is associated with the respective class model. Otherwise, it is rejected from the classifier and it is considered as a noise.

Results and Discussion

Training and testing sets

The classifiers used for the object recognition on the basis of their spectral characteristics are validated, trained and tested with the sets presented in Table 2.

Classification of the grain sample elements

The results from the classification of the grain sample elements using the three INTECHN classifiers and the three data models, as well as the results obtained by the Unscrambler referent platform, are presented in Figures 6 and 7. Figure 6 presents the results, when the non grain impurities are excluded from validation, training and testing sets. Figure 7 presents the results, when these grain sample elements are included in the procedures.

The classification error rate e_o is calculated using the equation:

$$e_o = \frac{\sum_{i=1}^N FN_i}{\left(\sum_{i=1}^N TP_i + \sum_{i=1}^N FN_i \right)} \quad (3)$$

where e_o gives the relative part of all incorrectly classified objects, where N is the number of classes, where FN_i is the number of elements from the i-th class, which are incorrectly classified to other classes; TP_i is the number of elements from the i-th class, which are correctly classified.

Table 2
Training and testing sets

Classes, subclasses	Training sets, number of objects	Testing set, number of objects
1cc	120	30
2cc	120	30
3cc	80	20
5cc	53	13
7cc	192	48
8cc	42	11
9cc	536	134
9cc1	96	24
9cc2	96	24
9cc3	96	24
9cc4	56	14
9cc5	96	24
9cc6	96	24

Analysis of the Results

INTECHN platform results obtained

The results obtained confirm the effectiveness of the developed approaches and procedures for features extraction, the classification strategy, classifiers and classifier validation. The errors of the grain sample testing set (1.3% when the non grain impurities are excluded from training/validation sets, and 7.3% when the non grain impurities are included in training/validation sets) are acceptable bearing in mind the specific experimental conditions and the diversity of the grain sample elements.

The comparative analysis of the results obtained using different variants of classifier validation, training and testing show that the data model, validation approach and the type of classifier influence on the classification accuracy.

For example, if the three data models, PCA,

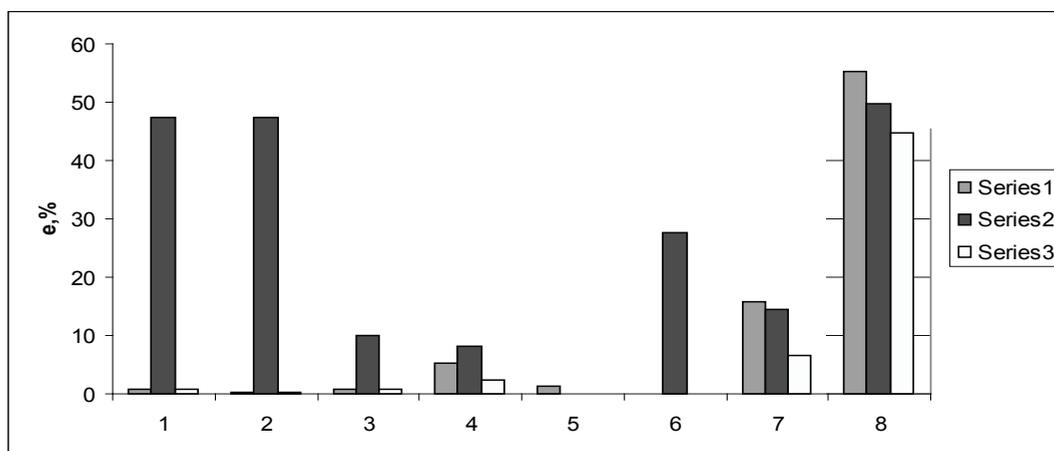


Fig. 6. Classification results obtained by the INTECHN and Unscrambler platforms.

Non grain impurities are excluded from the training/validation sets:

1-3- INTECHN training results: 1- PCA, 2-Wavelet1+PCA, 3-Wavelet2+PCA; s1- CDRBE, s2- CSRBE, s3- CRBEP; 4- Unscrambler training results; s1- PCA/ LDA, s2- PCA/ SIMCA, s3- PCA/ SVM;

5 and 6-INTECHN testing results: 5-non grain impurities are excluded from the testing sets, Wavelet1+PCA and CDRBE are selected; 6-non grain impurities are included in the testing sets, Wavelet2+PCA and CDRBE are selected; 7 and 8-Unscrambler testing results: s1- PCA/ LDA, s2- PCA/ SIMCA, s3- PCA/ SVM; 7-non grain impurities are excluded from the testing sets; 8-non grain impurities are included in the testing sets

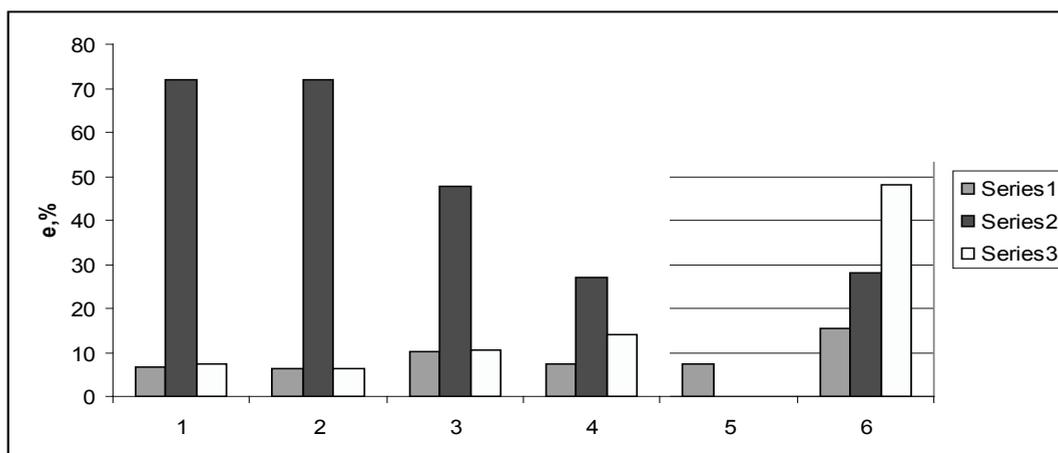


Fig. 7. Classification results obtained by the INTECHN and Unscrambler platforms.

Non grain impurities are included in the training/validation and testing sets:

1-3- INTECHN training results: 1- PCA, 2-Wavelet1+PCA, 3-Wavelet2+PCA; s1- CDRBE, s2- CSRBE, s3- CRBEP; 4- Unscrambler training results; s1- PCA/ LDA, s2- PCA/ SIMCA, s3- PCA/ SVM; 5 -INTECHN testing results, Wavelet1+PCA and CDRBE are selected; 6-Unscrambler testing results: s1- PCA/ LDA, s2- PCA/ SIMCA, s3- PCA/ SVM.

Wavelet1+PCA and Wavelet2+PCA are used, the training errors are 6.7%, 6.3% and 10.3% respectively using the CDRBE classifier and the non grain impurities are included in the validation.

The choice of the classifier influenced on the classification accuracy too. For example, the training errors obtained using the CDRBE, CSRBE and CRBEP classifiers and PCA data model were 6.7%, 72% and 7.2% respectively, when the non grain impurities are included in the validation.

The INTECHN validation approach (when the non grain impurities are included in the validation procedure, but they are excluded from the training sets) decreased the testing error 3.8 times (from 27.6% to 7.3%) in comparison with the traditional cross-validation approach (when the non grain impurities are simultaneously excluded or included in the validation and training sets).

Unscrambler platform results obtained

The training and testing errors obtained when the Unscrambler classifiers are used are bigger then the errors obtained by the CDRBE and CRBEP classifiers. For example, the SVM (the Unscramble classifier with the best performance)

and the CDRBE training errors are 2.5% and 0.8% respectively, when the elements from the class 9cc are excluded from the validation/training sets. The testing errors of the two classifiers are 6.6% and 1.3% respectively. When the elements from the class 9cc are included in the testing sets, the testing errors were 44.7% and 27.6%.

Similar results are obtained when elements from the 9cc class are included in the validation/training sets. For example, the SVM and CDRBE training errors are 14% and 6.3% respectively. The testing errors of the two classifiers were 47.9% and 7.3%.

Conclusions

An effective approach for grain sample quality assessment is developed. It is based on the analysis of the reflectance spectra of the grain sample elements. The approach is ground on the specific methods for feature extraction and for grain sample element classification. Combinations of two kinds of wavelet analyses and PCA are used for extracting appropriate features from object spectra. A method for pattern classification in classes located in a

noisy environment, which uses classifiers for class area approximation and a specific approach for classifier validation, is applied for the grain sample element classification. The effectiveness of the approach developed is confirmed by the results obtained in the recognition of maize grain sample elements under specific experimental circumstances. The training and testing accuracies are 93.7% and 92.7%, when the data model (Wavelet1+PCA) and classifier (CDRBE) selected are used. These results are acceptable bearing in mind the nature of the investigated objects. In comparison with the traditional cross-validation approach, the INTECHN validation approach decreases the testing error 3.8 times under specific experimental circumstances. In comparison with the Unscrambler referent platform, the INTECHN platform gives better results under specific experimental circumstances. For example, the SVM (the Unscrambler's classifier with the best performance) and CDRBE training accuracies are 97.5% and 99.2% respectively, when elements from the class 9cc are excluded from the validation/training sets. The testing accuracies of the two classifiers are 93.4% and 98.7%. When elements from the class 9cc are included in the validation/training sets, the training and testing errors are increased. The training errors of the two classifiers are 14% and 6.3% respectively, and the testing errors are 47.9% and 7.3%.

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