Improving the Grain Quality Assessment Fusing Data From Image and Spectra Analyses

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Abstract— **The paper presents approaches, methods and tools for assessment of main quality features of grain samples that are based on color image and spectra analyses. Visible features like grain color, shape, and dimensions are extracted from the object images. Information about object color and surface texture is obtained from the object spectral characteristics. The categorization of the grain sample elements in three quality groups is accomplished using two data fusion approaches. The first approach is based on the fusion of the results about object color and shape characteristics obtained using image analysis only. The second approach fuses the shape data obtained by image analysis and the color and surface texture data obtained by spectra analysis. The results obtained by the two data fusion approaches are compared.**

Keywords- grain sample quality assessment, color image analysis, spectra analysis, classification, data fusion

I. INTRODUCTION

The assessment of the food quality and safety is an important part of the food production chain. The higher food quality requirements demand the development of new, objective technologies for food quality assessment. In conformity with these requirements is the main goal of INTECHN project "Development of Intelligent Technologies for Assessment of Quality and Safety of Food Agricultural Products" founded by the Bulgarian National Science Fund. Computer based, express, objective, intelligent technologies, methods and tools for assessment of the 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 complex assessment of food products quality features. The first approach is based on analysis of object color images using a computer vision system. Visible features related to the color characteristics, shape and dimensions could be obtained because of such analysis. The second approach that uses analysis of object spectral characteristics can form information about object features related to the object surface color and texture characteristics. Fusing the results from two kinds of analysis, we can get more complete and accurate notion about main quality features.

A. *Problem statement*

According to the Bulgarian National Standards, the main quality features of maize grains are inherent for the variety appearance, shape, color, smell, taste, moisture, and impurities. Whole grains and broken grains (bigger than the half of the whole grain) which have inherent for the variety appearance, shape, and color are considered as normal grains (Table 1).

TABLE I. MAIZE GRAIN SAMPLE CLASSES AND SUBCLASSES

Normative classes
1cst - standard kernel (whole grains and broken grains bigger than the half of the whole grain,) with inherent appearance, shape and color for the variety
2cst-grain impurities: broken grains smaller than the half of the whole grain, heat-damaged grains, small grains, shriveled grains, green grains, sprouted grains, infected (with Fusarium) grains, smutty grains.
3cst- non grain impurities: corn-cob particles, leaf and stem fractions, pebbles, soil and sand, as well as harmful elements
Color classes
1cc- grains with inherent color for the variety, back side
2cc- grains with inherent color for the variety, germ side
3cc- heat-damaged grains
4cc- green grains
5cc- moldy grains
6cc- smutty grains
7cc- infected (with Fusarium) grains
8cc- sprouted grains
9cc- non – grain impurities
Shape classes
1csh- whole grains with inherent shape for the variety
2csh- broken grains bigger than the half of the whole grain
3csh- broken grains smaller than the half of the whole grain and small and shriveled grains
4csh- non – grain impurities

The grain impurities include broken grains (smaller than the half of the whole grain), heat-damaged grains, burned grains, small grains, shriveled grains, green grains, sprouted grains, and mouldy grains. The non-grain impurities include corncob particles, leaf and stem fractions, pebbles, soil, sand, and metal particles. Smutty grains, infected (with *Fusarium*) grains, as well as harmful elements (bunt) are included in the last grain sample group.

An expert based on its visual estimation evaluates the grain quality characteristics specified above (excluding smell, taste, and moisture). They are mainly related to the appearance, color characteristics, shape, and dimensions of the sample elements. The main trend in the last few years is to use Computer Vision Systems (CVS) and spectra characteristics analysis in order to evaluate such quality factors. To obtain a complex assessment of the grain quality using data about color characteristics, shape and dimensions of the grain sample elements, is a complicated and multilevel task. This is because the color characteristics, shape and dimensions of the elements in a sample vary within a wide range.

B. Overview of related works

Many results are published, in which color characteristics analysis is used to assess some particular quality features. In [20] a digital image analysis algorithm, developed to facilitate classification of individual kernels of Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats, and rye using textural features of individual grains is reported. The textural features of individual kernels are extracted from different colors and color band combinations of images to determine the color or the color band combination that gave the highest classification accuracies in assessment of authenticity of cereal grains. Color characteristics analysis is used also to assess variety [20, 21], infections [16], germination [15], weed identification [14], etc.

Morphological features, related to the grain shape and geometrical parameters are used for assessment of the grain variety. A set of eight morphological features namely, area, perimeter, length of major axis, length of minor axis, elongation, roundness, Feret diameter and compactness are presented in [10] to recognize five different kinds of cereal grains. A broader investigation, with a total of 230 features (51 morphological, 123 color, and 56 textural) used for classification of barley, Canada Western Amber Durum wheat, Canada Western Red Spring wheat, oats, and rye is presented in [11]. Assessment of the grain sample purity is performed by profile analysis of corn kernels using one-dimensional digital signals based on its binary images in [12], by modeling the shape using a set of morphological features in [11] and by shape curvature analysis in [16]. Computer vision methods are also used for determination of kernel mechanical damage and mold damage in [8], determination of broken kernels in threshing process in [7], etc.

Some preliminary investigations in [16] show that we can't get sufficiently precise assessment of some of grain sample elements like smutty grains, infected grains and non grain impurities using image analysis only. This is conditioned by the fact that a change of the color characteristics, as well as of the surface texture is appeared for these grain sample elements. It is difficult to detect the change of surface texture using CVS. That is why we expect a more accurate assessment of these sample elements to be obtained using spectra analysis. Unfortunately, information about object shape and dimensions cannot be extracted from spectra.

Visible (VIS) and near infrared (NIR) spectra analyses are applied in the assessment of different grain quality features in [6]. 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, mineral content, as well as for the detection of grain infections. Different calibration models for corn starch yield are developed for predicting corn starch content in [17]. In [22] authors used single-kernel near infrared spectroscopy (NIRS) to predict accurately the internal kernel composition. NIRS analysis is applied for predicting protein content, moisture content and flour color b* values [4]. In [9] a method for predicting the protein composition using NIR spectroscopy is developed. In [2] authors analyzed 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 kinds of mycotoxins like aflatoxin, fumonisin and others are very important tasks because mycotoxins are toxic for animals and humans. In [3] reflectance and transmittance VIS and NIR spectroscopy is used to detect fumonisin in single corn kernels infected with Fusarium verticillioides. Corn kernels are classified accurately as fumonisin positive or negative, respectively. A method for determination of Fusarium graminearum infection is proposed in [5]. 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. In [22] transmittance spectra (500 to 950 nm) and reflectance spectra (550 to 1700 nm) are evaluated as tools for aflatoxin determination in single whole corn kernels. Authors used 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. A NIRS method for estimation of sound kernels and Fusarium-damaged kernels proportions in grain and for estimation of deoxyinivalenol levels was proposed in [13]. The method classified sound and Fusarium damaged kernels with an accuracy of 98.8 and 99.9%, respectively. In [18] a neural network based method for deoxynivalenol levels in barley using NIRS from 400 to 2400 nm was developed. NIR spectra of barley samples with different deoxynivalenol levels from 0.3 to 50.8 ppm were analyzed. Fourier transform of NIRS for rapid and non-invasive analysis of deoxynivalenol in durum and common wheat was used in [1]. 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. In [19] a new method using NIR hyperspectral imaging system (960–1,700 nm) to identify five western Canadian wheat classes at different moisture levels is presented. The authors found that the linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) could 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 (PCA), 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), Quadratic Discriminant Analysis (QDA), Cluster Analysis (CA), Support Vector Machines (SVM), Neural Networks (NN), and Soft Independent Modeling of Class Analogy (SIMCA) are used for assessment of different grain features using data from grain spectra.

C. Paper content overview

This paper discus the INTECHN platform approaches, methods and tools for analysis of color images and spectral characteristics of the grain sample elements, as well as approaches for the fusion of the results from the two kinds of analysis. These approaches are illustrated in the assessment of main quality features of maize grain samples.

The paper is organized as follows. Section "Materials and Methods" describes the hardware system, methods for feature extraction from images and spectra and classification procedures used in the INTECHN platform. Two variants for fusing the results from color and shape analysis and one based on the results from object spectral characteristics and shape analysis are also presented in this section. All the proposed algorithms are experimentally evaluated and the results are presented in section "Results and Discussion". Finally, the last section shows the "Conclusions" of the paper.

II. Materials and Methods

A. INTECHN platform hardware

The INTECHN hardware system consists of the following main components: CVS and spectrophotometer (QE65000, Ocean Optics, USA). The CVS includes two color CCD cameras, which give a possibility to form color images of the investigated object in two planes (horizontal and vertical). An illuminate system is used for direct object illumination.

B. Grain sample classification groups

The characteristics of grain sample elements, which are on principle being evaluated by an expert, based on its visual estimation, are assessed using CVS within the frames of the INTECHN project. Groups (classes) and subgroups (subclasses) in which the elements of the maize grain sample have to be distributed are presented in Table 1.

It is evident from the table that the main determinative characteristics of grain sample elements are related to the object color and shape. Because of the fact that color and shape features are described in a different manner, it is advisably the assessment these characteristics to be made separately. After that, the results from two assessments have to be fused to obtain the result about object categorization to one of the normative classes. In terms of the classification procedure, color and shape groups are divided in several subgroups. Color object characteristics are separated in 8 basic classes corresponding to the typical for the different sample elements color zones and 1 additional class that corresponds to the non – grain impurities (it is impossible to define a compact class for non – grain impurities). According to the object shape, the objects are divided in 3 basic classes corresponding to the whole grains, broken grains bigger than the half of the whole grain and broken grains smaller than the half of the whole grain, and 1 additional class that correspond to the non – grain impurities. Each of the three basic shape classes is further divided in 6 shape subclasses.

C. Feature extraction from images

Several color models based on RGB (**R**ed-**G**reen-**B**lue) are used for separating object area from the background and for extraction of different color zones inside the object area (inherent for the variety color, heat-damaged grains, green grains, smutty grains, infected (with *Fusarium*) grains, bunt, non – grain impurities). Furthermore, four color texture models [16] are developed for this purpose. It is expected they will better underline zone color ratios in the input RGB image.

To represent the shape of the investigated objects, 10 – dimensional vector descriptions are used [16]. It is typical for the maize kernels that its contour has a huge asymmetry at the part where the germ exists and at the opposite part. It is easy to locate the germ in the whole grains and to build contour descriptions and models with proper orientation. For the broken grains, depending on what part of the whole is remaining (with the germ or without it) the contour descriptions could be sufficiently different. That is why it is necessary for classes 2csh and 3csh (to be more precise – for their corresponding subclasses) to define two types of descriptions and models: for shapes where the germ exists in the remaining part of the grain and where it is not. All the shapes of the investigated objects are divided into 18 groups (subclasses).

D. Features extraction from spectra and data dimensionality reduction

The classification of grain sample elements based on their spectral characteristics is made in groups corresponding to the color classes presented in Table 1.

The spectral characteristics of grain sample elements are vectors with about 1500 components. PCA and combination of Wavelet descriptions and PCA are used for extraction of typical features from object spectra and for reduction of input data dimensionality. 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 decomposition can vary from 1 to 4. The most informative Wavelet coefficients are chosen using the PCA method.

E. INTECHN platform classification procedures

INTECHN platform uses specific classification strategy, classifiers, and validation approach. They are conditioned by the specificity of the classification tasks concerning recognition of grain sample elements.

Classification approach. If the classes (built from color, shape, PCA and Wavelet+PCA descriptions) are presented in the feature space, a part of them (1cc, 2cc,…8cc) will form comparatively compact class regions. The sets of descriptions extracted from the grain sample training sets are used for developing the models of these grain sample groups. Each class model is presented by the class centre (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. A correct model for the 9cc class could not be created because of the fact that the spectral characteristics of elements of this class could be sufficiently different in each subsequent grain sample.

As a correct model for the 9-th grain group could not be created, a part of the descriptions of such objects from the testing set could get into the boundaries of the other eight classes defined. A big part of them would get outside the class regions and could be located in a random place in the feature space. These descriptions could be considered as noisy vectors. It could be assumed that the comparatively compact class regions of the objects from the first eight groups are submerged in a noisy environment. Therefore, the task for categorization of the grain sample elements 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 LDA, CA, SVM, KNN and some other methods, which build boundaries between class regions, is obviously not a good choice. This is because for the class 9cc, which correspond with the 9-th grain group, a correct model cannot be created.

The task for grain class modeling is reduced to a task for approximation of the grain class regions. For this purpose, classifiers based on Radial Basis Elements (RBEs) are used. Such classifiers are chosen in terms of the simplicity of the classification procedure and the accuracy of the class region 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 vectors will be included within the class boundary and it is easy to change the dimensions of the particular class region.

INTECHN platform classifiers. In the frames of the INTECHN platform different variants of a neural classifier based on Radial Basis Elements (RBEs) are used for class area approximation. The following classifiers [16] are used for class areas approximation.

Classifier with standard RBEs (CSRBE). Only one RBE is used for approximation of each class area The CSRBE approximates round shaped classes only. To determine to what class the input vector belongs the output $f\omega i$ with maximum value is chosen. This value has to exceed the threshold value Δ which determines the class areas dimension.

Classifier with decomposing RBEs (CDRBE). Another solution for class area approximation gives the classifier architecture with decomposing RBEs. The CDRBE classifier gives a possibility to form classes which dimensions along the directions of separate coordinate axes are different. Changing the RBEs biases and the threshold value Δ we can vary the class shape from sphere to shape close to parallelepiped.

Classifier with RBEs which takes into consideration the (CRBEP). The CRBEP classifier approximates the class regions using standard (or decomposing) RBEs and takes into consideration the class potentials. The number of vectors in each of the classes, accumulated during the classification process, is interpreted as a class potential. It introduces an additional correction of the assessment formed by i-th RBE. The effect of the correction comes down to the displacement of the boundary between the two overlapping parts of class regions. The displacement depends on the ratio of accumulated number of vectors in each of the classes.

Validation approach. The classifiers presented in this section are trained and validated using a specific cross-validation procedure. The goal of the validation is to select the appropriate data model and classifier, as well as to obtain the optimal classifier parameters.

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

F. Fusing the results from color and shape analyses

Because of the fact that color and shape features are described in a different manner, the assessment of these characteristics is made separately. After that, the results from the two assessments have to be fused in order to obtain the object's final categorization to one of the normative classes.

Different variants for fusing the results from color and shape analysis of grain sample elements are developed at different stages of the investigation. The algorithms developed could be associated with hierarchical clustering algorithms. Their typical feature is that different criteria for class merging are used at different levels of data fusion.

Variant 1. A comparatively simplified fusion scheme is used in the first algorithm. It is presented in Fig. 1.

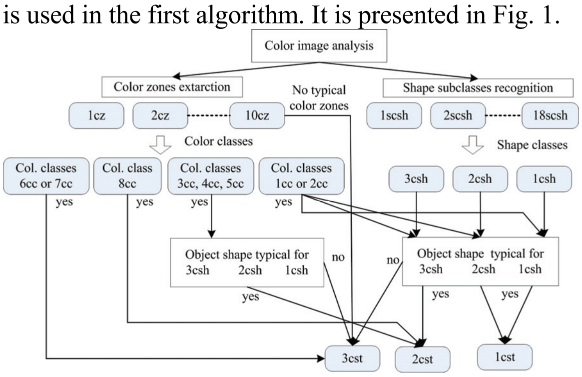

Figure 1. Fusing the results from color characteristics and shape analysis. Variant 1.

The input data (input classes) are separated in two groups – color characteristics data and objects shape data. The first group consists of 10 color zones inherent for the maize grains. The second group consists of 18 shape subclasses (1scsh, 2scsh… 18scsh). The first six of them correspond to different shape models of whole kernels, the next six – to models of broken grains bigger than the half of whole grain and the last six – to models of broken grains smaller than the half of the whole grain.

The color class (1cc, 2cc… 8cc) is determined based on preliminary defined combinations of color zones at the first stage of fusing the results from the color analysis. The shape subclasses are merged into one of the three main shape classes (1csh, 2csh, and 3csh).

At the second stage of the analysis, the fusion of color and shape classes is made in order to form the final decision of object classification in one of the three normative classes (1cst, 2cst, and 3cst). The assessment whether the shape of the object is typical for one of the three main grain classes or not is used as a fusion criterion for color classes 1cc to 5cc. For 6cc, 7cc and 8cc classes the shape is not important at all.

Variant 2. The second algorithm (Fig. 2) uses color and combined topological models of typical color zones. The topological models represent the plane distribution of the color zones within the object area. A set of color topology models (when 3 or more typical for the kernels color zones are found) and combined topology models (when only 2 typical color zones are found) is preliminary defined. The combined topological models represent the plane distribution of some shape element (kernel prickle or rear area) and the color zones found.

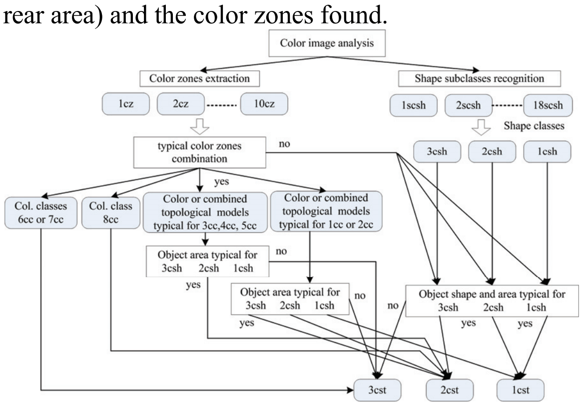

Figure 2. Fusing the results from color characteristics and shape analysis. Variant 2.

The final objects categorization when such topology is found is performed without taking into account the object's shape but only its area. The shape and area are the most important for the final categorization of the objects when only one typical color zone is found. When the object belongs to 6cc, 7cc or 8cc its shape is not important at all for taking the decision.

Variant 3. The third data fusion algorithm (Fig. 3) is based on data about object color characteristics obtained trough analysis of their spectral characteristics and data about object shapes extracted from object images. This variant of color and shape data fusion is conditioned by the fact that the recognition of color class of grain sample elements using spectral data is more precise.

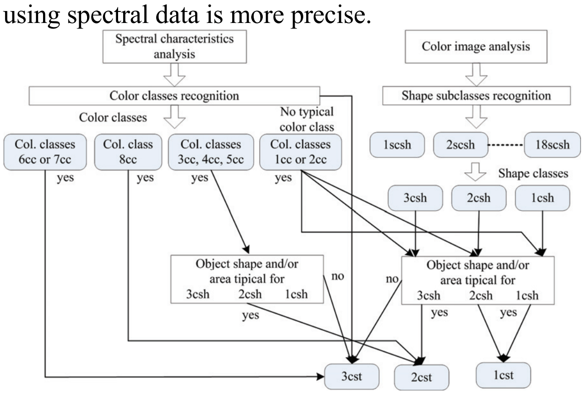

Figure 3. Fusing the results from color characteristics and shape analysis. Variant 3

The main criterion for the final categorization is the object color class. The correspondence of object shape and/or area to the typical for the different shape classes shape and area is an additional criterion.

III. Results and Discussion.

A. *Training and testing sets.*

The developed procedures for assessment of grain sample quality are validated, trained, and tested with sets presented in Table 2.

TABLE II. Training and Testing Sets

Color class recognition							
Classes	***1cc***	***2cc***	***3cc***	***5cc***	***7cc***	***8cc***	***9cc***
Train. sets	10	10	12	15	18	19	
Test. sets	47	81	44	24	74	39	168
Object shape classification							
Classes	***1csh***	***2csh***	***3csh***	***4csh***			
Train. sets	120	135	135				
Test. sets	122	63	11	256			
Classification in normative classes							
Classes	***1cst***	***2cst***	***3cst***				
Test. sets	117	118	242				

B. *Color and shape class recognition*

Classification error rates of color class recognition using the selected classifier (CDRBE) and image and spectra analyses the validation procedure are presented in Fig. 4. The "Training/Testing errors1" represents the results when the group of non-grain impurities is excluded from the training/testing sets, while the "Training/Testing 2" represents the results when this group is included in the training/testing sets.

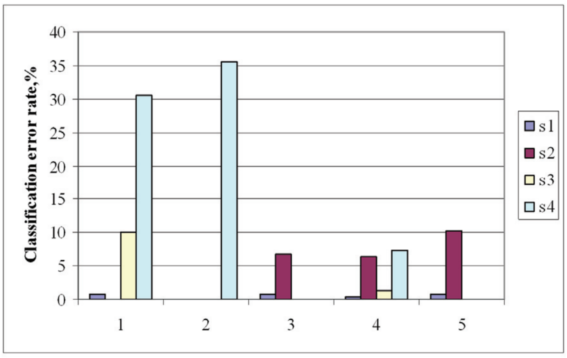

Figure 4. Classification errors of color and shape class recognition using image and spectra analyses: 1-color class recognition using image analysis; 2-shape class recognition using image analysis; 3-color class recognition using spectra analysis (PCA), ; 4-color class recognition using spectra analysis (Wavelet1+PCA) ; 3-color class recognition using spectra analysis (Wavelet1+PCA A); s1- training errors1, s2- training errors 2, s3- testing errors 1, s4 testing errors2

The classification error rate e_o is calculated using the equation (1). e_o gives the relative part of all incorrectly classified objects, were N is the number of classes, FP_i is the number of elements from other classes assigned to the i-th class, TP_i is the number of correctly classified elements from the i-th class, FN_i is the number of elements from the i-th class classified incorrectly to other classes.

$$e_o = \frac{\sum_{i=1}^{N} FP_i}{\left(\sum_{i=1}^{N} TP_i + \sum_{i=1}^{N} FP_i\right)} . \qquad (1)$$

1) *Analysis of the results.*

1. The testing results concerning object color zones extraction and color class recognition using CVS are acceptable, bearing in mind the nature of the investigated objects. The error e_o=10% is obtained without elements from class 9cc in testing set. When we include such kind of elements (168 in number), the classification error increases to 30.6%. This result is due to the fact, that in a big part of non-grain impurities color zones typical for the different grains are found.

2. The selection of a proper classifier for color class recognition has a significant influence over the classification accuracy for training and testing. In color class recognition using CDRBE, training and testing errors decrease with 6.2% and 35.1% comparing to CSRBE [16]. When we train and test classifiers, CRBEP do not show its advantages

because during these two procedures the data for different classes is being processed consecutively. When classifying unknown objects the input vectors will be processed in a random way so it is expected for CRBEP to perform better than the other two.

3. The testing results concerning shape class recognition show that the rate of objects from class 1csh assigned to other classes is comparatively small (4.9%). On the other hand, the rate of objects assigned to this class, which actually belong to other classes, is sufficiently bigger (35.2%). The rate of objects from class 3csh assigned to 2csh and 4csh is big too.

4. The classification error of objects from class 3csh (parts of kernels) is large. This is an expected result because it is impossible to define some standard shape for objects from this class. In many cases, even a qualified expert will not recognize such objects if no color characteristics but only shape is taken into consideration. During the classifier training, models of broken kernels are created based on whole kernel models and that is why the training sample classification error rates for classes 2csh and 3csh are small. This is the explanation of the big difference between training and testing classification results for these two classes.

5. The testing error obtained using spectra analysis (7.3%) is acceptable bearing in mind the specific investigation conditions and the diversity of grain sample elements.

6 The comparative analysis of the results obtained using different variants of classifier validation, training and testing confirms the effectiveness of the INTECHN classification strategy, classifiers, validation approach and data models. For example, if we use the three data models: PCA, Wavelet1+PCA and Wavelet2+PCA the training errors are 6.8%, 6.3% and 10.3% respectively using the CDRBE classifier. The INTECHN validation approach (when the non – grain impurities are included in validation procedure, but are excluded from training sets) decreases the testing error 3.8 times (from 27.6% to 7.3%) in comparison with the traditional validation approach (when the non – grain impurities are simultaneously excluded or included in validation and training sets). The choice of an appropriate classifier for specific classification task has an influence over the classification accuracy too. For example, the training errors obtained using the CDRBE, CSRBE and CRBEP classifiers and PCA data model are 6.8%, 72%, and 7.3% respectively.

7. The classification errors for color class recognition using spectra analysis are sufficiently smaller than the errors using image analysis. For example, the testing errors are 1.3% and 10% respectively using the two approaches when the non – grain impurities are excluded from the validation and testing sets. When we include the non – grain impurities in validation and testing sets these two errors are 7.3% and 42%. The big difference between the two errors can be explained by the fact that the object spectral characteristics contain not only information for objects color characteristics, but for their surface texture too. Although typical for some grain groups color zones are found in a big part of non – grain impurities, the surface texture of these elements is sufficiently different from the typical for the grains.

C. Classification in normative classes.

The results from objects classification (when non – grain impurities are included in testing sets) in normative classes when the selected classifiers and the three variants of data fusion are used, are presented in Table 3.

TABLE III. CLASSIFICATION ERRORS IN NORMATIVE CLASSES

Color and shape data fusion			
Fusion variant	***Variant 1***	***Variant 2***	***Variant 3***
Selected data model	***RGB***	***RGB***	***Wavelet1+PCA***
Selected classifiers	***CDRBE– CRBEP***	***CDRBE– CRBEP***	***CRBEP- CDRBE***
Errors	***Test. errors,%***	***Test. errors,%***	***Test. error,%***
e_o,%	15.3	8.6	5.3

1) Analysis of the results:

1. The object classification in normative classes (1cst, 2cst, and 3cst) involves complex assessment of color and shape characteristics of the investigated objects. Color and shape data are fused together for this purpose. The data fusion procedure improves sufficiently the final classification results. The classification error rate e_0 in normative classes using CVS (Selected variant CDRBE– CRBEP) is 15.3% when data fusion Variant 1 is used and 8.6% when Variant 2 is used, while the errors of object color zones extraction and object shape recognition are 41,9% and 35.6% respectively.

2. The choice of an appropriate procedure for fusion the results from color characteristics and objects shape analysis has a significant influence over the final classification accuracy. When we use Variant 3 for class recognition, the classification error rate e_0 decreases 1.6 times in comparison with the best results obtained using CVS. This is because the spectra analysis gives the best results for color class recognition.

IV. CONCLUSIONS

The results from investigations at this stage of the INTECHN project implementation concerning estimation of grain sample quality using complex assessment based on color image and spectra analysis can be summarized as follow:

1. The developed approaches, methods, and tools for grain samples quality assessment based on the

complex analysis of object color, surface texture, and shape give an acceptable accuracy under specific experimental circumstances.

The error rate e_o=5.3% of the final categorization in the normative classes can be accepted as a good result at this stage of project implementation.

2. The data fusion procedure improves sufficiently the final classification results. The classification error rate e_0 using CVS is 15.3% when Variant 1 is used and 8.6% when Variant 2 is used, while the errors of object color zones extraction and object shape recognition are 41,9% and 35.6% respectively.

3. The results obtained show that the choice of an appropriate procedure for fusion the results from color characteristics and objects shape analysis has a significant influence over the final classification accuracy. When we use the second algorithm (Variant 2), which is based on color zones topology assessment the classification error rate decreases 1.8 times compared to the first algorithm (Variant 1) in which color class assessment is based on the registration the presence of the typical color zones combinations only. When we fuse the results from color class recognition obtained using spectra analysis and shape class recognition obtained using image analysis (Variant 3) the final classification accuracy is increased 2.9 and 1.6 times in comparison with Variant 1 and Variant 2 respectively.

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