Image segmentation of agricultural products using statistical indicators

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Abstract: *Machine inspection is a mandatory technological process in industrial processing agriculture products. The camera detects color and shape based irregularities of the object resulting in a large number of parameters for decision-making and sorting product compliance. The goal was to discover a new criterion for decision-making using only the output signal of the RGB camera. Research employed the digital images of raspberries, blackberries, peas and yellow beans during real processing, obtained from a color sorter machine. The visual texture of the surface of the agricultural products was described via defined statistical indicators of color (color average value (Avg), standard deviation (Stdv), entropy (E), and lacunarity (L) was used from the sphere of image fractal analysis as one of the criteria. By applying the non-parametric tests: Wilcoxon signed rank and Friedman test, statistically significant difference was established for the L and E criteria between compliant and non-compliant industrial products.*
Keywords*: COLOR, AGRICULTURE PRODUCTS, SORTING, MACHINE VISION.*

1. Introduction

The need to introduce automatic sorting of fruits and vegetables is becoming more and more pronounced in the world. For this purpose, various non-destructive methods of inspection of agricultural products in technological lines have been developed. One of them is machine vision, which is a promising control tool [1, 2].

This type of inspection is based on the analysis and processing of images with multiple types of implementation in the agricultural industry. Inspection machines in industrial plants, color sorters, mainly rely on cameras, some on lasers, and some on a combination of cameras and lasers, as well as a combination of positions above or below the product being selected. The camera detects irregularities based on the color of the object, while the lasers are oriented to structural features and can detect insects, animal parts as well as stalks, stones, paper, plastic, metal and glass, even if they are the same color as the product of interest.

In general, the external quality of fruits and vegetables is assessed mainly through physical characteristics: color, texture, size, shape and visual defects [3-5]. Willingness to buy food mostly depends on the sensory characteristics of the product, ie. mainly from the color that represents the subjective feeling of each consumer [6]. Color can be considered an indicator of freshness and ripeness of the fruit [7], as well as the texture, smell and taste [8, 9]. Descriptive parameters can be created through color parameters, and statistical measures are in most cases mean and standard deviation. These characteristics (properties, attributes) of agricultural products can be represented by numerous values, while statistical methods represent the basis for predicting and classifying sets of these values - data. Texture is the most suitable physical characteristic that can be interpreted through various statistical measures.

Texture analysis can play an important role in identifying and segmenting defective objects when selecting agricultural products [9-11]. The main goal of this research was to find a new criterion by combining already used parameters in research conducted in this and other areas, based on which agricultural products could be distinguished, as well as to separate non-compliant products and foreign facilities from harmonized ones. One similar attempt at a general classification of agricultural and food products is presented in the paper [12]. At the microstructural level under the defined experimental conditions described in the paper, the authors were able to make a division of certain food products based on fractal dimension (FD) values.

2. Materials and methods

The input data used in the research are digital images of agricultural products taken with the Optyx3000 color sorter during industrial processing. The color sorting and inspection system is part of an automatic line for inspection and packaging with a capacity of 3 t/h, in the ITN Eko Povlen factory in Kosjeric. The system captures images measuring 1024x1024 pixels in RGB format, and the scanning speed is 4000 Hz.

Based on the captured images, the machine recognizes compliant and detects non-compliant bio products. Non-compliant impurities include: wood, plastic, metal, glass, insects and animals or animal parts, plant products that have a similar color and shape (for example in peas - lat. *Solanum nigrum* which is toxic), as well as products that do not have the desired color (eg. yellow or dark overripe peas, etc.), stalks on a product of larger dimensions than allowed, moldy and infected products, etc.

After obtaining the first results based on images of raspberries that were published in the paper [13], the research was supplemented with images of peas, yellow beans and blackberries. The main goal was to describe the texture of organic products based on certain mathematical measures and to perform the recognition of harmonized fruits and classification according to defined categories.

The selected agricultural products for the purposes of this research are of different textures, colors and shapes.

The ranking of the evaluated samples is divided into three categories: harmonized, non-compliant and foreign impurities. Figure 1 shows a part of the analyzed images for the first two categories. An additional division of raspberry images into two subcategories has been introduced. The first refers to raspberries in which an opening can be observed at the place where the stalk was, and the second to raspberries in which this opening cannot be detected, in order to determine whether there is a statistically significant difference in the proposed criteria. A special category III is formed for foreign impurities that can be found during the inspection, such as stalks, earth, stone, plastic, paper, glass and the like.

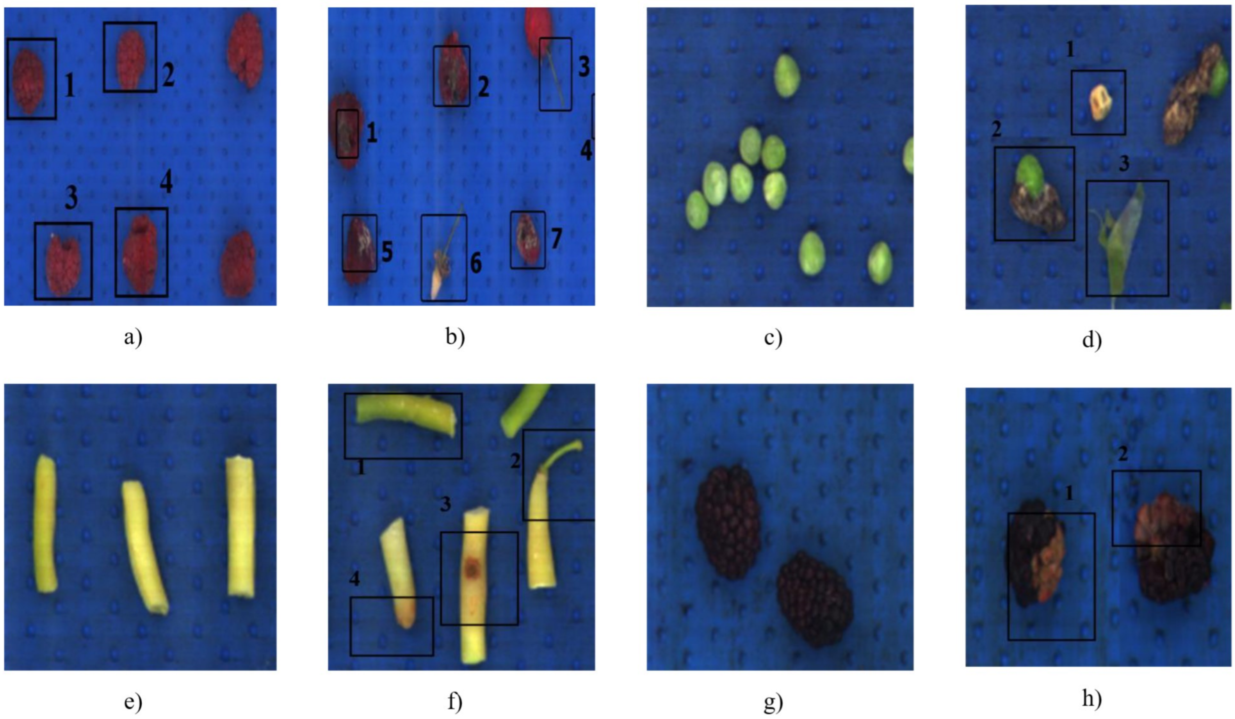


Fig. 1 *Part of analysed images: a) acceptable raspberry (1,2- sample without a hole; 3,4-sample with a hole) b) unacceptable raspberry (1,2,4,5,7- example of mold and damage; 3,4- Example of stalk) c) acceptable peas d) unacceptable peas (1-wilted; 2-moldy; 3-pod part) e) acceptable yellow beans f)unacceptable yellow beans (1- immature; 2-stalk; 3,4-bruises) g) acceptable blackberry h) unacceptable blackberry (1,2-damaged)*

In the Fig. 2 is presented schematic view of the proposed algorithm for analyzing digital images.

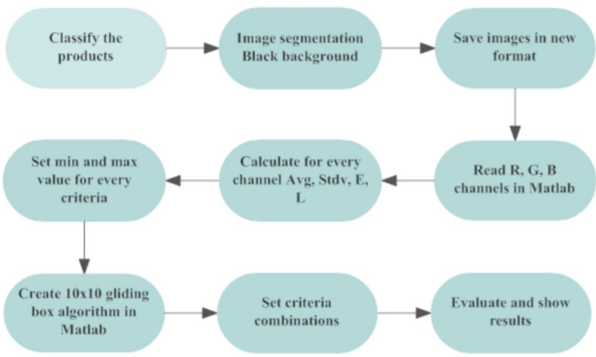


Fig. 2 *Proposed algorithm*

AdobePhotohop® was used for the first iteration of image analysis, where regions of interest were extracted. Next step was to set up black background. Each raspberry and blackberry as well as all impurities that can be found on inspection, were separately saved images as 70x70 px in size, 8-bit in their original .bmp format. Peas images were saved as 30x30 px in size and yellow beans as 30x100 px digital images. The Matlab® program was used for further analysis, extracting individual values of colors *r, g, b* (red, green and blue). Since color can be extracted from each pixel of the region of interest, those variables emerge in order to express the degree of heterogeneity.

Most of the studies show the result of measurements as the average color and its standard deviation from all the pixels selected in the region of interest [14, 15], this standard deviation being mainly a consequence of the heterogeneity instead of the measuring error.

Entropy was calculated for all channels separately using Matlab® where has already built-in function. Entropy is a statistical measure of randomness [16] that can be used to characterize the texture of the image. For the range of values of parameters r, g, b from 0-255, entropy is defined via the following equation (1):

$$E = -\sum_{i=0}^{255} p(i) log_2 p(i) \qquad (1)$$

where p (i) is the part of the pixel that takes the value of i, and $\log_2$ is the base 2 of the logarithm.

Further, the calculation of the following statistical indicators was performed for each individual color: average value (*Avg*), standard deviation (*Stdv*) and entropy (*E*). The aim was to find a correlation between standard deviation and average value. Same formula for lacunarity, which are used on binary images in fractal geometry, was applied. The name lacunarity comes from the Latin name lacuna, which in translation means lack, gap or hole [17]. It can be defined as a measure of the heterogeneity of a structure or the degree of structural variation within an object. In this case, that criterion was marked as *L* and calculated separately for each *r*, *g*, *b* channel, refer to (2).

$$L = \left(\frac{Stdv}{Avg}\right)^2. \qquad (2)$$

Also, statistical tests were performed for each criterion in order to confirm or deny normal distribution, based on which further use of statistical parametric or non-parametric tests is established. Because of smaller-size samples <50, the Shapiro-Wilk test was employed, which is more convenient. Then, descriptive analysis was carried out of all mentioned potential criteria. The significance of difference of the examined criteria among samples was checked using Wilcoxon sign rank test. Statistical analysis of the results was performed in the computer program IBM SPSS® 21.0 and MSExcel® 2013. After obtained results were checked and analyzed, we made a hypothesis that appropriate image segmentation can be done according to the criteria *L* and *E*. Further, the range of values (min to max) was defined for the first category of acceptable products. Also, results were tested by combination of other proposed criteria.

The next step was to develop the algorithm in Matlab®, the so-called gliding box algorithm, because the texture can be considered in a region and not in individual pixels. For the calculation of defined image color parameters I(x, y), to start with, a square was chosen 10x10px in size. The initial square is located at point (0, 0), in the upper left-hand corner. The algorithm records *Avg*, *Stdv*, *E* i *L* for every channel: *r*, *g*, *b* that are associated with the image underneath the moving window. If the parameters coincide with a specified range of values, the square is colored with a chosen color, in our case it was yellow to make the image better. The window is then translated by one pixel to the right and the underlying mentioned statistical measure is again recorded. When the moving window reaches the right-hand side of the image, it is moved back to its starting point at the left-hand side of the image and is translated by one pixel downward. The computation proceeds until the moving window reaches the lower right-hand edge of the image, at which point it has explored every one of its possible positions, i.e., to the endpoint (x_{m-9}, y_{n-9}). Due to product's different dimensions, the best box size for each product and criterion were investigated. As above mentioned, the initial box surface amounted to 10x10 px and final 2x2 px.

Algorithm: Pseudo code for image analysis and application of 10x10 box

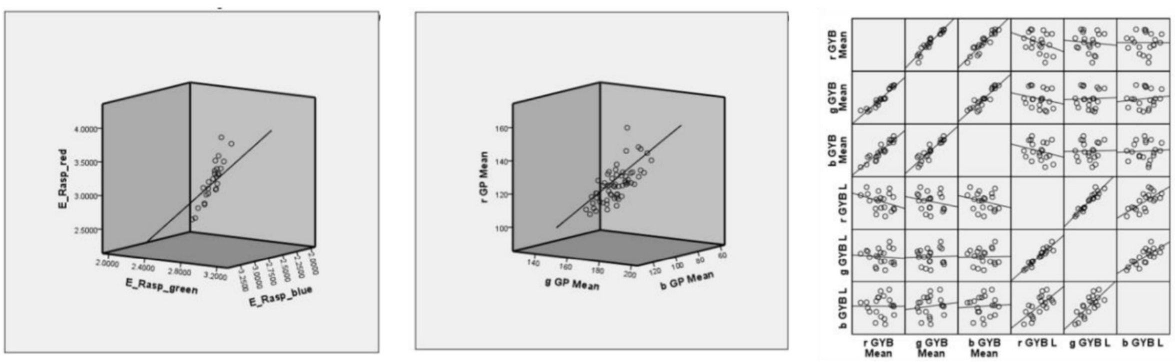
```
x1 = read the image
redChannel = extract red channel values x1
greenChannel = extract green channel values x1
blueChannel = extract blue channel values x1
cols = number of columns
rows = number of rows
for for each box 10x10 pixels in the image calculate
    redAvg, greenAvg, blueAvg = mean values of the current
    box 10x10
    redStd, greenStd, blueStd = standard deviation of the
    current box 10x10
    redE, greenE, blueE = entropy of the current box 10x10
    redL, greenL, blueL = (std/avg)^2 of the current box 10x10
    if redL between min and max redL
        and greenL between min and max greenL
        and blueL between min and max blueL
        current box 10x10 color the pixels yellow
    end if
end for
replace the input image
```

3. Results

Based on descriptive analysis results for all categories and the Shapiro-Wilk test, the criteria L and E, for every *r, g, b* channel, were found to have normal distribution in category I products for blackberries, peas and yellow beans (Sig .> 0.05). In the case of raspberries, only for criterion *E* is the assumption of normality of distribution confirmed. Products of categories II and III do not have normal distribution. Based on Wilcoxon's test, a statistically significant difference was found between category I raspberries with and without opening according to the *L* parameter for all three channels (r channel: $Z = -3.553$, $p < 0.05$; g channel: $Z = -2.725$, $p < 0.05$; b channel: $Z = -2.788$, $p < 0.05$;). The difference in the criterion of the mean value of *Avg* and entropy *E* was not statistically significant. In general, a low *L* value of the criterion suggests a homogeneous texture, while a high *L* value suggests a heterogeneous texture, but it should be noted that heterogeneous objects on larger scales may appear homogeneous and vice versa. Therefore, the value of criterion *L* can be considered as a measure of heterogeneity or scale-dependent texture.

Based on the previously presented result, it can be assumed that the parameter L, calculated in the already explained way, takes into account the variations in the figure, such as in this case the aperture. In the following statistical tests, raspberry data with and without holes will be considered together.

Further research addressed the question of whether there is a statistically significant difference between category I and category II products according to the defined criteria for all three *r, g, b* channels. Wilcoxon's rank test was also used for this question, where it showed a statistically significant difference (Sig. <0.05; $p < 0.05$) when it comes to raspberries, blackberries and yellow beans for parameters *L* and *E*.



a) b) c)

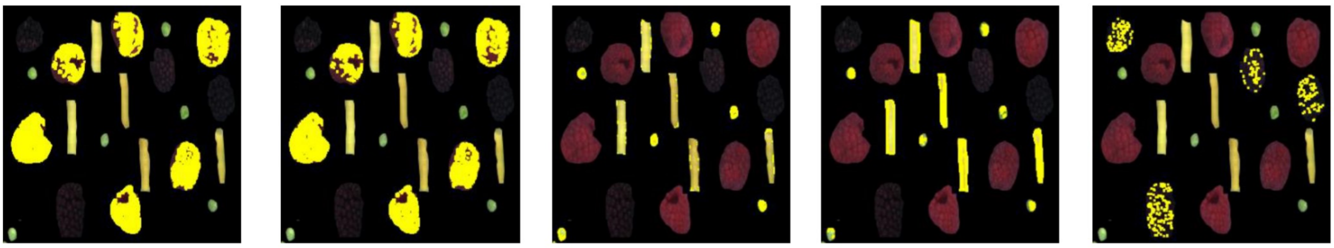
Fig. 3 *a) 3D Scatter of entropy of raspberry; b) 3D Scatter of entropy of peas; c)Scatter plot matrix of Avg and L r, g, b channel of yellow beans.*

Table 1: *Proposed criteria and values*

		Avg	E	L
Raspberry without a hole	R min	81	2,1346	0,0159
	R max	132	3,9744	0,0536
	G min	31	1,7569	0,0230
	G max	45	3,4214	0,0700
	Bmin	42	1,7980	0,0156
	B max	59	3,4094	0,0515
Raspberry with a hole	R min	82	2,3990	0,0228
	R max	136	4,0230	0,0809
	G min	31	2,0988	0,0207
	G max	46	3,5442	0,0752
	Bmin	42	2,1382	0,0182
	B max	60	3655	0,0589
Peas	R min	99	1,2648	0,3514
	R max	167	2,4417	0,1624
	G min	132	1,2795	0,0260
	G max	193	2,4596	0,1300
	Bmin	66	1,2412	0,0166
	B max	129	2,376	0,1279
Yellow beans	R min	122	1,6603	0,0369
	R max	212	3,7743	0,0764
	G min	132	1,6411	0,0346
	G max	205	3,6752	0,0740
	Bmin	43	1,5022	0,0366
	B max	102	3,3803	0,0648
Blackberry	R min	18	1,6012	0,0504
	R max	45	3,3223	0,1668
	G min	17	1,4488	0,0230
	G max	25	3,0280	0,0700
	Bmin	21	1,4599	0,0323
	B max	32	3,1493	0,0969

Based on these conclusions, the following criteria are proposed: *min* and *max* values of *L*, *Avg* and *E* from *r*, *g*, *b* parameters obtained from images of fruits that belong to category I of acceptable products as well as their combinations. Each product was checked over seven combinations of these criteria. The application of independent *Avg*, *L*, *E* criteria, combinations: *L+E*, *Ag+E*, *Avg+L*, *Avg+L+E* for all three channels *r,g,b*. Also, for each combination the optimum box algorithm size was investigated to yield the best results, starting from 10x10 px to 2x2 px.

Raspberry without a hole | Raspberry with a hole | Peas | Yellow beans | Blackberry



2x2 px box | 2x2 px box | 2x2 px box | 2x2 px box | 4x4 px box

Fig. 4 *Representation of resulting images by applying the best combination of criteria and box size*

According to the table of proposed ranges for criteria values, Tab.1, it can be concluded that there occur particular overlaps in two or more investigated products. For that reason, we have created several test images with all investigated good products, so as to reach an ideal combination of criteria that can be used to describe each product independently. An example of such image is given in Fig. 4. In investigating some combinations or an independent criterion for a single product, more than one product was recognized in the test image. Figure 5 shows images with criteria and box size that produced best results of recognition for each group of individually investigated product.

Good result means appropriate formation of the product shape when marking with yellow color. The application of the proposed algorithm allowed good recognition of raspberries and blackberries using a combination of criteria *Avg+E*. In raspberries the best result was produced by the box size 2x2px and in blackberry by 4x4px, and only these products were recognized with those box sizes and criteria. As for peas and yellow beans, none of the criteria combinations or box sizes gave satisfactory result. In the figures shown, the best result was yielded approximately by combination *Avg+E* , and thereby both products were recognized nearly equally in the image.

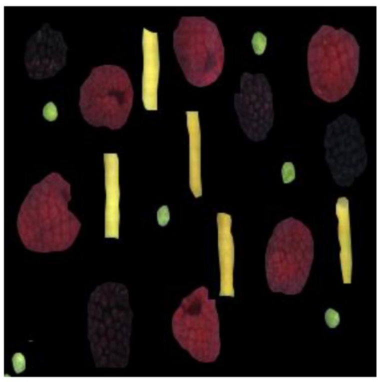


Fig. 5 *Example of test picture*

Next, separate test images were created for each agricultural product, which contains several products from each category that were randomly selected (Fig. 6 *a* and *b*).

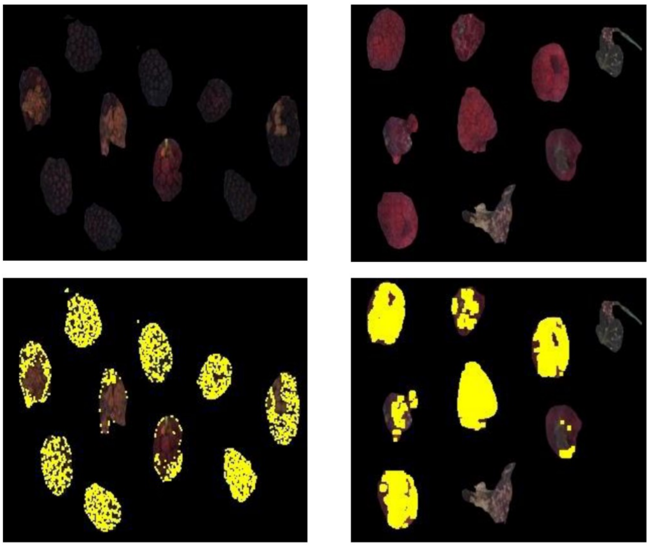


Fig. 6. *a) blackberry image test, b) raspberry image test, c) application of Avg + E and 2x2 box, d) application of Avg + E and 4x4 box.*

Based on the final results, several conclusions can be drawn. The values of *L* and *E* differ statistically significantly between the proposed categories of compliant, non-compliant product and foreign material in each tested agricultural product. By applying the proposed model, using the sliding square algorithm and selected input criteria, the combination of *Avg+E* criteria gave a satisfactory result in the detection of harmonized parts of raspberry and blackberry fruits. Conditionally satisfactory results were in the recognition of raspberries and blackberries in relation to the other two agricultural products, peas and yellow beans. The proposed model is not suitable for all products, primarily due to different product sizes.

The study [18] compared the performance of the system in classifying fifteen types of fruits and vegetables based on eight color and texture parameters. The combination of color and texture parameters proved to be the best, as in this paper, which confirms the conclusion that it is not possible to obtain a satisfactory result by using only morphological characteristics for identification. According to the results in the paper [19], a set of color and texture characteristics also gave a satisfactory outcome when it comes to recognition, but the texture parameters for each color channel were considered individually. The subject of the research was only one product, potato chips, and it was observed in certain experimental conditions. For each class, a different set of characteristics was influential. Finding a unique general combination of criteria ("fingerprint") for the classification of agricultural products requires much larger data sets.

4. Conclusion

The current situation, however, shows that classical methods for classifying fruits and vegetables have been developed for a limited number of fruit classes and small sets of products. Using only morphological features for identification, these varieties could not provide good enough results.

The proposed idea and algorithm have a range of advantages and disadvantages, which gives room for further research and improvement. The results showed that the color and morphological feature, as entropy, alone were not able to recognize different products with high accuracy. However, the combination with average values certainly can show acceptable results for particular products, in our case raspberry and blackberry. It can be conclude that there is significant differences in the values of proposed criteria between good and bad product that can be used for further research. Problem with same recognition of pea and yellow beans can be attributed to a similar range of color values between yellow and green values in RGB color scale, which also reflected similar ratios of the proposed criteria *L* and *E*. The good side of the algorithm can be adequately recognized product boundaries by optimizing the box size and increasing the number of samples. For future research, it is necessary to carry out more experiments using a larger number of samples and different conditions to complete a study.

In addition, there is the idea of generalizing the recognition of different agricultural products based on the solution found, ie. that the values of the obtained criterion or combination of criteria be the only solution for the general differentiation of agricultural products. Despite the variability of influential parameters in the paper, one of the conclusions is that statistical modelling of parameters by further research can lead to more significant results in the evaluation of agricultural products, confirmed statistically significant difference in the proposed criteria *L* and *E*, has the potential for further research.

ACKNOWLEDGMENT

This research was supported by the Serbian Ministry of Science and Technological Development – project by contract 451-03-68/2020-14/200105.

5. References

[1] A.S.M. Shafi, M.M. Rahman Recognition and Classification of Fruit Diseases Based on the Decomposition of Color Wavelet and Higher-Order Statistical Texture Features. In: *Uddin M., Bansal J. (eds) Proceedings of International Joint Conference on Computational Intelligence. IJCCI 2019*. Alg. for Int. Sys. Springer, Singapore. (2020)

[2] M. Khojastehnazhand, H. Ramezani. Machine vision system for classification of bulk raisins using texture features, J. of Food Eng. **271** (2020)

[3] M. Teena, A. Manickavasagan, A. Mothershaw, S. El Hadi, D. S. Jayas, Potential of machine vision techniques for detecting fecal and microbial contamination of food products: A review, Food and Biop. Tec. **6** (2013)

[4] D. Markovic, N. Mladenovic, V. Simonovic, I. Markovic, S. Stevanovic. Fruit flow calculation on the rotating sizing machines. Tec. Gaz. **21** (2014)

[5] S. Khoje. Appearance and characterization of fruit image textures for quality sorting using wavelet transform and genetic algorithms, J. of Tex. St., **49** (2017)

[6] S. Shella, S. Meghashree, I. Monica, A. Prathima, K. Shriya. Automation for sorting of objects using raspberry pi3, Int. J.of Adv. in Elec. and Com. Sci., Special Issue. (2016)

[7] R. Valadez-Blanco, A.I.S. Virdi, S.T. Balke, L.L. Diosady. In-line colour monitoring during food extrusion: sensitivity and correlation with product colour. Food Res. Int., **40** (2007)

[8] R. Banerjee, B. Tudu, R. Bandyopadhyay. A review on combined odor and taste sensor systems. J. of Food Eng., **190** (2016)

[9] B. Zhang, W. Huang, J. Li, C. Zhao, S. Fan, J. Wu, C. Liu. Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review. Food Res. Int., **62** (2014)

[10] S.R. Dubey, A.S. Jalal. Apple disease classification using color, texture and shape features from images. *SIViP* **10** (2016)

[11] D. Singla, A. Singh, R. Gupta. Texture Analysis of Fruits for Its Deteriorated Classification. In: *Woungang I., Dhurandher S. (eds) International Conference on Wireless, Intelligent, and Distributed Environment for Communication. WIDECOM 2018*. Lecture Notes on Data Eng. and Comm. Techn.. **18**. Springer, Cham. (2018)

[12] R. Quevedo, L.G. Carlos, J.M. Aguilera, L. Cadoche. Description of food surfaces and microstructural changes using fractal image texture analysis, J. of Food Eng. **53** (2002)

[13] I. Markovic, D. Markovic, J. Ilic, V. Simonovic, E. Veg, G. Šiniković, N. Gubeljak. Application of Statistical Indicators for Digital Image Analysis and Segmentation in Sorting of Agriculture Products, Tech. Gaz, **25** (2018)

[14] V. Kumar, P. Gupta. Importance of Statistical Measures in Digital Image Processing, Int. J. of Em. Tech. and Adv. Eng. **2** (2012)

[15] A. Girolami, F. Napolitano, D. Faraone, A. Braghieri. Measurement of meat color using a computer vision system, Meat Sci., **93** (2013)

[16] J. Steinbrener, K. Posch, R. Leitner. Hyperspectral fruit and vegetable classification using convolutional neural networks. Com. and El. in Agr. **169** (2019)

[17] B.B. Mandelbrot. The Fractal Geometry of Nature. W.H. Freeman, New York, (1987)

[18] S. Arivazhagan, S. Newlin, S. Nidhyanandhan, L. Ganesan. Fruit Recognition using Color and Texture Features. J. of Em. Tr. in Com. and Inf. Sci., **1** (2010)

[19] F. Mendoza, P. Dejmek, J. Aguilera. Colour and image texture analysis in classification of commercial potato chips, Food Res. Int. **40** (2007)