THE INFLUENCE OF ILLUMINATION PARAMETERS ON THE PERFOMANCES OF COLOR SORTING MACHINES

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Abstract: The color recorded in the image is not an inherent value of observed object, because it is also influenced by the illumination properties, as well as geometry and surfaces of neighboring objects. Numerous studies have developed and investigated image processing procedures in color sorting machines, where as not many of them have considered the influence of illumination on numerical values related to the colors. In this paper, parameters related to the color of corn have been examined. In each image, the corn has been illuminated by one of four different types of light sources. And different luminous intensities of each type of light source have been applied. The processing of obtained images has been performed in MATLAB, and parameters of images in RGB, CIE L*a*b* and HSV color space have been analyzed. Further descriptive statistics analysis has been performed by IBM SPSS. The variations of parameters with the change of light intensity, showed no statistical significance. The change of the type of the light source has a significant impact on all analyzed features.

Keywords: SORTING, CORN, COLOR SPACE, ILLUMINATION

1. Introduction

In qualitative evaluation of agricultural products, many methods, based on evaluation of their main physical properties, has been developed. The morphological, optical and image texture features are useful in quality inspection, identification, classification, discrimination and differentiation between cultivars, varieties, etc. [1- 4]. Francis [5] found that human perception could be easily fooled. Together with the high labor costs, inconsistency and variability associated with human inspection, accentuates the need for objective measurements systems. The most successful and most widely utilized methods are the optical methods which incorporate high-speed optical sensing and data processing techniques to facilitate high-speed quality evaluation and sorting of many agricultural products with a high degree of accuracy [6].

The color is an important quality factor in differentiating between the acceptable and unacceptable agricultural product, and it has been widely studied [7 - 11]. Human eye perceives three colors: red, green and blue, and others synthesizes by mixing these three colors. Different papers presented methods and researches performed in different color spaces such as RGB, HIS, HSV, CIELAB and many others. Many researches were comparing effectiveness of some of these color spaces in color sorting and came to different results. Bianconi [12] has shown that the basic statistical methods, applied on RGB color space parameters, can be the best practice in approaching the color sorting problem. In regard to the problem of automatic classification of materials such as ceramic tiles, based on color, Lopez [13] has got satisfactory results using RGB and CIELAB color space.

Corn is one of the leading products in agriculture production in Serbia and has a yield of 7.951.583 t in 2014. [14]. Since the sorting is one of the fundamental operations during industrial processing, many researchers is trying to find appropriate, non-destructive, simple and cheap method based on good color recognition.

When capturing color images, proper light source is important since the color of the food sample depends on the part of spectrum reflected from it [15]. The perception of color of any object depends on illumination which is utilized. The idea of this paper is to examine the influence several types of illuminations on color of the image of the product. This paper also presents the attempt to investigate the impact of the intensity of illumination on agricultural product image parameters. Of many image parameters, the parameters of RGB, Lab and HSV color spaces were chosen to be evaluated.

2. Materials and methods

In this paper, the color of defrosted corn, which had been frozen to -18℃, has been investigated. The products were put in black chamber, of dimensions 50x50x50 cm. Olympus VG-110 camera was used. As the illumination Philips bulbs, of color rendering index (CRI) Ra8, and color temperature 2700K were used. Table 1 shows other primary characteristics of illuminations, as well as abbreviated notification of used illumination. The snapshots was taken at the distance of 40 cm from products, in dark room, on temperature 15℃. Total measurements were performed within 10 minutes.

Table 1: *Main features of the applied illumination*

Types of illuminatio n	Power (W)	Luminous flux (lm)	Luminous intensity (cd)	Notification of illumination	
				1 bulb	2 bulbs
Clear	60W	655		c1	c2
Reflector	60W		750	r1	r2
Soft White	60W	630		sw1	sw2
Warm White	14W=68W	856		ww1	ww2

Once the color images of the corn samples were captured, pictures were cropped to form the same portions of each image of dimensions 50x50 pixels using Adobe Photoshop® 7.0. Thus, the obtained images are further processed in the program Matlab®, where the color was analyzed qualitatively and quantitatively. A digital color image is represented in RGB form with three components per pixel in the range 0 to 225 and conventionally stored using eight bits per color component. Each parameter of color: red, green and blue is presented in the form of 50x50 matrix. Further statistical analysis where performed in IBM SPSS® 21.0. It was necessary to switch square matrix to column matrix, which has been performed in Matlab and then matrix extracted in Office Excel 2007, because SPSS have possibility for uploading data from Office Excel. Schematic presentation of algorithm is shown in figure 1.

By subsequent transformation of the images into CIELAB color space, values of *L, a**, *b** parameters for each pixel were obtained. L* defines lightness, a* denotes the red/green value and b* the yellow/blue value. These values were used to calculate chroma and hue angle from equations 1 and 2.

(1) $$C^* = \sqrt{a^{*2} + b^{*2}}$$

(2) $$h^\circ = arctg(b^* / a^*)$$

The *c** represents *Chroma* or 'saturation'. It ranges from 0 at the centre of the circle, which is completely unsaturated (i.e. a neutral grey, black or white) to 100% at the edge of the circle for very high Chroma (saturation) or 'color purity'. The h^* axis represents *Hue*.

The units for h^* are degrees (angular), ranging from 0° (red) through 90° (yellow), 180° (green), 270° (blue) and back to 0° [15].

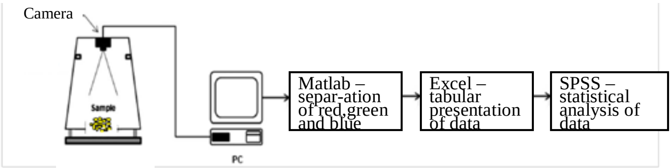


***Fig. 1.** Shematic view of procedure*

The first step in this research was to examine whether the data for each of parameters deviate from normality, because many statistical analyses are based on assumption that the distribution of the values of dependent variables is normal. Normality can be evaluated partly based on the calculated values of indicators like skewness and kurtosis. According to Garson [17], distributions are normal if their skewness is in range [-2,+2], although some authors use the more stringent requirement that a narrower interval [-1,+1]. Also according to Garson, normal distribution characterized kurtosis in range [-2,+2] (some authors use more lenient criteria [-3,+3], and others authors use stricter criteria [-1,+1]). The resulting an non-normal distribution is usually obtained when it comes to a large number of samples such as this case. Within the first analysis, descriptive analysis of values was performed. In further analyzes, two non-parametric test were used: Wilcoxon signed-rank test and Friedman test. Both tests are appropriate for determining whether or not there is a significant association between a dichotomous variable and a continuous variable with independent samples data.

3. Results and discussion

In table 2, taken images of examined corn in format 50x50 pixels under different illumination are shown. With visual method we can see differences between illuminations, while differences between the illuminations by one or two bulbs are unclear.

***Table 2.** Display samples of corn captured under different illumination*

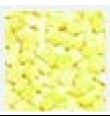
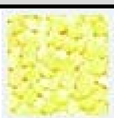
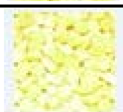
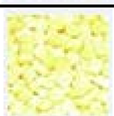
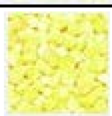
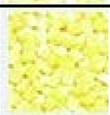
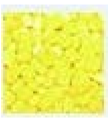
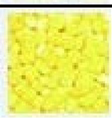
Type of illumination	1 bulb	2 bulbs	Resolution
Clear			50x50
Reflector			50x50
Soft White			50x50
Warm White			50x50

Figure 2 gives a perspective view of L, a^*, b^*, c and h values associated with basic colors.

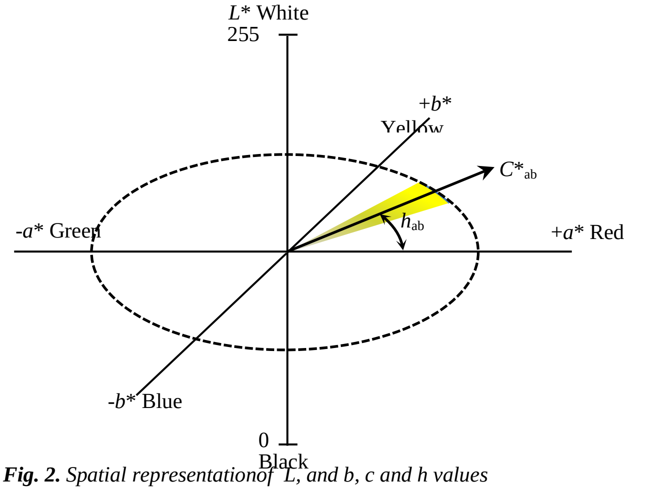


***Fig. 2.** Spatial representation of L, and b, c and h values*

After analyses of data using descriptive analysis, based on skeweness and kurtosis in range [-1, +1], we came to conclusion that distribution is not normal for all test color values. Weather the distribution is normal or not, we can see on histograms and some other diagrams which we can obtain from descriptive analysis Explore in IMB SPSS. All normal distributions are symmetric and have bell-shaped density curves with a single peak and a lower number of results towards to the ends (tails) bell [18] and with Normal Q-Q Plot, higher the bar of observed results closer to a straight line, it is closer to a normal distribution. For example, figure 3 and 4 show histogram and Normal Q-Q Plot of blue value when reflector light was used with single bulb, where we conclude that the distribution is not normal.

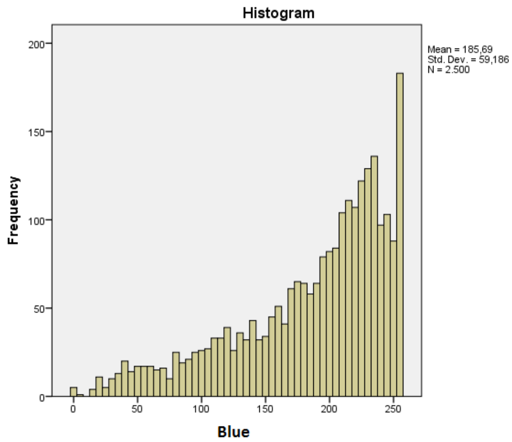


Fig. 3. Histogram for blue value under reflector light with single bulb

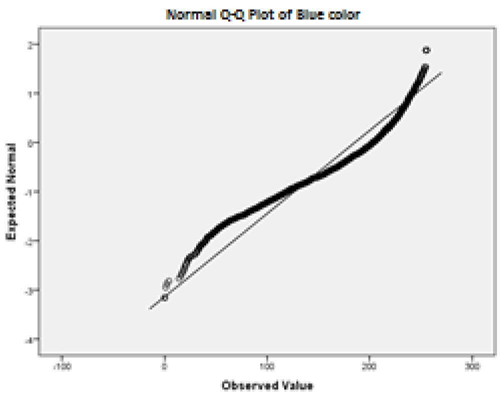


***Fig. 4.** Normal Q-Q plot for blue value under reflector light with single bulb*

Results of descriptive statistics are summarized in table 3 for RGB values, and in table 4 for CIELAB values and in table 5 for Chroma and Hue angle.

Table 3. *Descriptive Statistics for RGB value*

	Min	Max	Mean	Std. Dev.
Red c1	173	255	240,63	11,231
Red c2	179	255	240,60	10,732
Red r1	175	255	243,01	10,847
Red r2	184	255	243,21	10,491
Red sw1	181	255	240,19	10,614
Red sw2	173	255	240,51	11,148
Red ww1	172	255	236,63	9,198
Red ww2	179	255	236,33	9,798
Green c1	139	255	243,73	15,405
Green c2	148	255	243,30	14,400
Green r1	145	255	245,95	13,023
Green r2	142	255	246,12	12,836
Green sw1	124	255	242,46	14,441
Green sw2	140	255	243,61	14,476
Green ww1	126	255	239,06	14,004
Green ww2	141	255	238,95	15,279
Blue c1	2	255	134,62	47,457
Blue c2	0	255	130,48	44,003
Blue r1	11	255	161,87	45,191
Blue r2	23	255	162,16	45,028
Blue sw1	0	255	122,32	39,095
Blue sw2	0	255	130,48	44,585
Blue ww1	0	219	69,89	25,059
Blue ww2	0	216	72,06	25,257

Table 4. *Descriptive Statistics for CIELab value*

	Min	Max	Mean	Std. Dev.
L c1	156	255	240,30	12,886
L c2	167	255	239,88	12,025
L r1	161	255	243,01	11,428
L r2	159	255	243,17	11,228
L sw1	148	255	239,01	11,940
L sw2	156	255	240,07	12,186
L ww1	143	253	235,04	11,002
L ww2	162	252	234,93	11,970
a* c1	102	144	116,46	5,021
a* c2	101	147	116,30	4,828
a* r1	104	140	118,36	4,746
a* r2	103	139	118,38	4,588
a* sw1	102	150	115,90	4,510
a* sw2	102	148	116,13	4,825
a* ww1	101	140	113,37	4,513
a* ww2	102	146	113,38	4,893
b* c1	126	216	178,84	17,672
b* c2	123	216	180,66	16,513
b* r1	123	215	167,71	17,718
b* r2	124	214	167,66	17,603
b* sw1	124	214	184,09	14,311
b* sw2	126	213	180,72	16,608
b* ww1	145	216	203,34	7,745
b* ww2	146	215	202,58	7,588

Table 5. *Descriptive Statistics for chroma and hue angle*

	Min	Max	Mean	Std. Dev.
chroma c* c1	178	245	213,78	13,291
chroma c* c2	179	243	215,18	12,411
chroma c* r1	179	242	205,70	12,509
chroma c* r2	179	243	205,65	12,566
chroma c* sw1	181	246	217,77	10,996
chroma c* sw2	180	244	215,14	12,453
chroma c* ww1	191	244	232,87	6,492
chroma c* ww2	189	245	232,23	6,394
Hue angle h c1	44	64	56,73	3,494
Hue angle h c2	43	65	57,05	3,270
Hue angle h r1	42	63	54,56	3,799
Hue angle h r2	43	63	54,56	3,737
Hue angle h sw1	43	64	57,68	2,771
Hue angle h sw2	44	64	57,09	3,279
Hue angle h ww1	49	64	60,83	1,609
Hue angle h ww2	51	64	60,73	1,632

Since the surface color of a corn is highly heterogeneous due the complex distribution of water, starch, reducing sugars, etc., principally, it is generally important to compute the average color which is representative of the complete surface. Also, it is useful to know standard deviation of investigated parameters. Since standard deviation is a measure that is used to quantify the amount of variation or dispersion of a set of data values, the illumination and the color parameter that gives the smallest standard deviation of parameters are those that offer the best definition of a color. A standard deviation close to 0, indicating that the data points tend to be very close to the mean value, is preferable, concerning the definition of color, while a high standard deviation indicates that the data points are spread out over a wider range of values, making it harder to define unacceptable color.

In tables 3, 4 and 5, maximum value are marked. There it can be concluded that the light reflector gives the most intense RGB values and the *chroma* and *hue angle* most pronounced in warm white light, and that the standard deviation is the lowest for *a** value that represents the yellow color.

Since the studied product is corn, it is required more specific values of yellow color. According to *r*, *g*, *b* values it is harder to get the exact values of acceptable color, while using *b**, *c* i *h* we can define optimal range aceptable values and a visual display in the spatial diagram. Based on average values and standard deviation, the most intensive yelow color give warm white illuminant, where the standard deviation are lowest. Taking into account table 1, and with visual method lead to the same conclusion. The illumination gives a warm tone and therefore the more intensive experience of color, so that *b** value that defines the yellow are the largest, like it is expected. However, based on small standard deviations, we can conclude that the warm white illumination is the most appropriate to define the optimal range of hue values of yellow.

After descriptive analysis, test of Frequency was performed, where it can bee seen which values are the most frequent and with minimum deviations. Data analysis and histogram shows that the most of invesigated data gave large range and large deviations of values. Minimum range clustered values give *Hue angle*, *Chroma* and *b** values for warm white illuminations. Example of histograms are given in figures 5, 6 and 7.

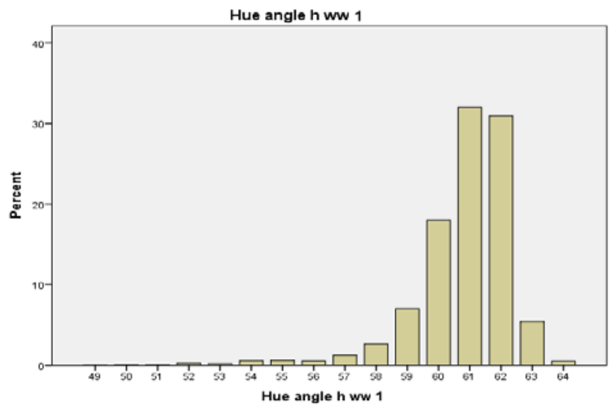


Fig. 5. *Hue angle of warm white illumination with one bulb*

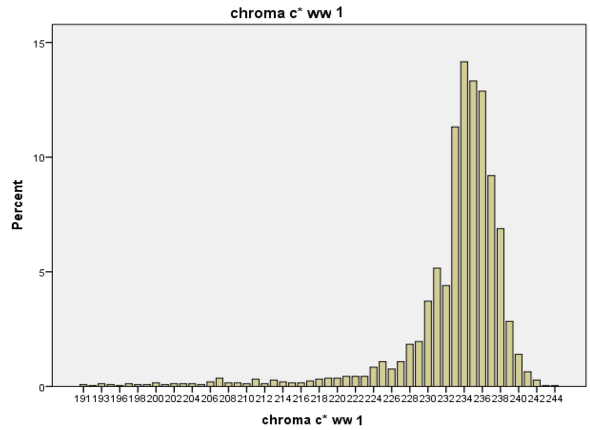


Fig. 6. *Chroma of warm white illumination with one bulb*

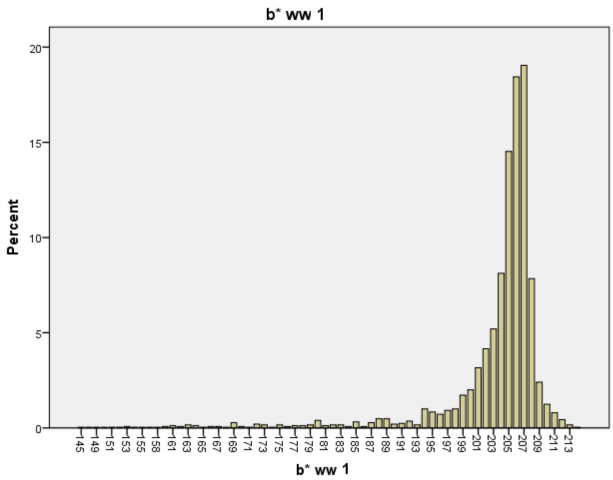


Fig. 7. *b* value of warm white illumination with one bulb*

Based on histograms of *hue angle*, *chroma* and *b** values, it can be defined range of color values and then based on that range in the further research, we can define good color of product.

As it has already been mentioned, with visual method it cannot be seen difference between pictures with one bulb and two bulbs. In order to examine it using statistics, color parameters were evaluated with Wilcoxon signed-rank test and showed a statically significant change in some cases. The results of this test are presented in tables 6, 7, and 8.

Table 6. *Wilcoxon signed-rank test for R,G,B values*

	Red c2 - Red c1	Green c2 - Green c1	Blue c2 - Blue c1
Z	-0,838[b]	-4,008[b]	-7,702[b]
Asymp. Sig. (2-tailed)	0,402	0,000	0,000
r	-	0,06	0,11
	Red r2 - Red rs1	Green r2 - Green r1	Blue r2 - Blue r1
Z	-0,697[c]	-1,886[c]	-0,846[c]
Asymp. Sig. (2-tailed)	0,486	0,059	0,398
r	-	-	-
	Red sw2 - Red sw1	Green sw2 - Green sw1	Blue sw2 - Blue sw1
Z	-2,586[c]	-7,837[c]	-17,614[c]
Asymp. Sig. (2-tailed)	0,010	0,000	0,000
r	0,04	0,11	0,25
	Red ww2 - Red ww1	Green ww2 - Green ww1	Blue ww2 - Blue ww1
Z	-1,402[b]	-1,214[c]	-8,113[c]
Asymp. Sig. (2-tailed)	0,161	0,225	0,000
r	-	-	0,11

a. Wilcoxon Signed Ranks Test
b. Based on positive ranks.
c. Based on negative ranks.

Table 7. *Wilcoxon signed-rank test for L, a*b* values*

	L c2 – L c1	a* c2 - a* c1	b* c2 - b* c1
Z	-4,677[b]	-1,931[b]	-8,155[c]
Asymp. Sig. (2-tailed)	0,000	0,053	0,000
r	0,07	-	0,11
	L r2 – L r1	a* r2 - a* r1	b* r2 - b* r1
Z	-1,798[c]	-0,309[c]	-0,373[b]
Asymp. Sig. (2-tailed)	0,072	0,757	0,709
r	-	-	-
	L sw2 - L sw1	a* sw2 - a* sw1	b* sw2 - b* sw1
Z	-9,084[c]	-3,117[c]	-17,845[b]
Asymp. Sig. (2-tailed)	0,000	0,002	0,000
r	0,13	0,04	0,25
	L ww2 - L ww1	a* ww2 - a* ww1	b* ww2 - b* ww1
Z	-0,934[c]	-0,083[b]	-11,642[b]
Asymp. Sig. (2-tailed)	0,350	0,934	0,000
r	-	-	0,16

Table 8. *Wilcoxon signed-rank test for Chroma and Hue angle*

	chroma c* c2 – chroma c* c1	Hue angle h c2 - Hue angle h c1
Z	-8,761[c]	-6,569[c]
Asymp. Sig. (2-tailed)	0,000	0,000
r	0,12	0,09
	chroma c* r2 – chrom c* r1	Hue angle h r2 – Hue angle h r1
Z	-0,524[b]	-0,112[b]
Asymp. Sig. (2-tailed)	0,600	0,910
r	-	-
	chroma c* sw2 - chroma c* sw1	Hue angle h sw2 - Hue angle h sw1
Z	-19,232[b]	-14,221[b]
Asymp. Sig. (2-tailed)	0,000	0,000
r	0,27	0,2
	chroma c* ww2 - chroma c* ww1	Hue angle h ww2 - Hue angle h ww1
Z	-10,440[b]	-4,701[b]
Asymp. Sig. (2-tailed)	0,000	0,000
r	0,15	0,07

Significant difference is present when Asymp. Sig. (2-tailed) – is below $p<0{,}005$ (red cells) and the degree of the difference is determined by the value of r which is defined by equation 4. According to Cohen (1988) [19] criteria, the differences does not have influence, if r is close to 0,1 or it is is less than 0,1. This is the case for almost all types of illumination and color parameters except in three cases where there is a medium impact when r approaches to the value of $r=0{,}3$ and that is the case in the following cases: blue sw1-sw2, b*ww1-ww2 i chroma c*sw1-sw2, as it is marked as green cells in tables 6, 7 and 8.

$$r = \frac{Z}{\sqrt{N}} \tag{4}$$

Next analysis, related to the examination with Friedman test, gives the answer on question whether there is difference between the images made with different illuminations. This test is appropriate to test the significance of the association between a categorical variable ($k \geq 2$). The statistically significant for all values (Asymp. Sig. (2-tailed) is below 0,005, according to which concludes that there is statistically significant difference between values of applied illuminations. The example was given in table 9 for L^* value when the clear illuminations with one bulb applied.

***Table 9.* Example for L value using Friedman test**

Test Statistics[a]

N	2500
Chi-Square	1990,415
df	3
Asymp. Sig.	0,000

a. Friedman Test

Friedman test shows differences in calculated values but it does not show exactly between which types of illumination and in what extent. The answers to these questions are obtained by applying Wilcoxon signed-rank test.

Of all the results of Wilcoxon signed-rank test, only the values where effect size are r≥0,2, which represents medium effect size, and r≥0,5 which represents a large effect size (red cells), are shown in tables 9, 10 and 11.

***Table 9.* Wilcoxon signed-rank test and level of significance for red, green and blue values**

Red	r	Green	r	Blue	r
wwb1 - r1	0,39	ww1 - c1	0,27	r1 - c1	0,31
wwb1 - sw1	0,35	ww1 - r1	0,4	sw1 - c1	0,25
ww2 - c2	0,29	ww1 - sw1	0,33	ww1 - c1	0,59
ww2 - r2	0,38	ww2 - c2	0,29	sw1 - r1	0,53
ww2 - sw2	0,33	ww2 - r2	0,37	ww1 - r1	0,61
		ww2 - sw2	0,37	ww1 -sw1	0,61
				r2 - c2	0,39
				ww2 - c2	0,41
				sw2 - r2	0,41
				ww2 - r2	0,61
				ww2 - sw2	0,61

***Table 10.* Wilcoxon signed-rank test and level of significance for L, a* and b* values**

L	r	a*	r	b*	r
ww1 - c1	0,33	ww1 - c1	0,34	r1 - c1	0,34
sw1 - r1	0,29	sw1 - r1	0,32	sw1 - c1	0,27
ww1 - r1	0,47	ww1 - r1	0,48	ww1 - c1	0,6
ww1 - sw1	0,43	ww1 - sw1	0,38	sw1 - r1	0,55
ww2 - c2	0,33	ww2 - c2	0,36	ww1 - r1	0,61
ww2 - r2	0,45	sw2 - r2	0,27	ww1 - sw1	0,6
ww2 - sw2	0,45	ww2 - r2	0,47	r2 - c2	0,41
		ww2 - sw2	0,36	ww2 - c2	0,6
				sw2 - r2	0,44
				ww2 - r2	0,61
				ww2 - sw2	0,6

***Table 11.* Wilcoxon signed-rank test and level of significance for chroma c* and hue angle h* values**

c*	r	h*	r
r1 - c1	0,34	r1 - c1	0,32
sw1 - c1	0,28	ww1 - c1	0,56
ww1 - c1	0,6	sw1 - r1	0,52
sw1 - r1	0,55	ww1 - r1	0,6
ww1 - r1	0,61	ww1 - sw1	0,57
ww1 - sw1	0,61	r2 - c2	0,38
r2 - c2	0,41	ww2 - c2	0,56
ww2 - c2	0,61	sw2 - r2	0,41
sw2 - r2	0,44	ww2 - r2	0,6
ww2 - r2	0,61	ww2 - sw2	0,57
ww2 - sw2	0,61		

4. Conclusion

Sample images were processed in MATLAB by implementing the explained algorithm. In this algorithm for color analysis of samples, different combinations of color spaces and intensity transformation functions were applied on the images. The digital imaging method allows measurements and analyses of the color of food surfaces that are adequate for food engineering research. While it is not yet a adequate substitute for sophisticated color measurement instruments, it is an attractive alternative due to its simplicity, versatility, and low cost. In IBM SPSS all the approaches achieved factory compliance exceeding 95% minimum accuracy. The preliminary results of this study are useful information for future development of the quality control technique in practical usage.

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