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Theses of Ph.D dissertation

Method development for monitoring the roasting process of coffee and for the detection of barley that may occur as impurity in coffee

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1. Introduction

Coffee is one of the world's most widely consumed beverages; some consumes it because of its taste, others for stimulant effect of caffeine in coffee. In Hungary, the annual coffee consumption per capita is on a declining trend since 2007, according to CSO data, it decreased from 2.7 kg to 2.3-2.2 kg between 2000 and 2012. The 70% of the world coffee production is based on Arabica coffee. It is considered as better quality coffee than Robusta due to its richer and more intense flavour, less bitter taste related to lower caffeine content, therefore its market price is higher. Depending on the geographical origin of Arabica coffee prices can be twice or even ten times higher than the Robusta's. The coffee flavour depends beyond on the raw material and how it is processed, mostly on roasting, or it may be defective beans and foreign material influence.

For coffee roasters the experimentation of improved coffee mixture is very important because it can give a special taste experience to the consumer that can highlight the brand from competitors' product. However it is difficult to maintain the composition that has the same organoleptic profile in the future roasting processes because of the heterogeneous nature of the raw material.

Although the two coffee species or the impurities in coffee can be differentiated easily as a bean, in ground form it becomes a more difficult task. Coffee producers can also benefit from this fact when they distribute their coffee in ground roasted form, maybe mixed with impurities (similar to coffee) in a weaker period to compensate somewhat from the lost revenue.

Several methods were applied to monitor the coffee roasting process or to detect impurities in coffee, however, these methods are usually complicated or require laborious sample preparation. Consequently, there is a need to replace the methods requiring high chemical consumption with correlative, fast methods like electronic tongue or optical methods.

Based on the literature gaps were discovered in the determination of coffee roasting degree, and in the fast detection of impurities in coffee. Therefore, it is necessary to develop methods, which can monitor the roasting process on-line and can indicate the end of the process to achieve the quality required by consumers. The other fast method should detect possible foreign material mixed to coffee, thus it can be used as a routine during quality control.

2. Research aims

The aims of my PhD work are the following: to develop fast methods based on electronic tongue and optical methods that makes possible to monitor the colour and taste changes of coffee occur during roasting, and to detect foreign material causing taste changes in coffee, therefore be able to determine the fact and the rate of coffee adulteration.

Further targets are to develop a rapid and easy to use portable device applicable to

- detect impurities in coffee (especially ground roasted barley)
- monitor coffee roasting process.

Therefore it is able to help authorities to detect products with incorrect labelling (incorrect mixing ratio), thus to avoid confusion for consumer.

As well as by monitoring the roasting process, the instrument can be applied to produce a quality coffee expected by the consumer.

3. Materials and methods

3.1. Materials

Materials for my experiences were supported by Sara Lee Hungary Kft. and Café Frei; commercial samples were also purchased.

1.2 kg of raw 100% Arabica coffee (provided by Café Frei, Hungary) was divided into six batches and roasted at different levels (light: L1, L2, L3, intensive/dark: D1, D2, D3). Arabica coffees roasted at six different levels and five commercial 100% Arabica coffee samples from different brands (B1, B2, T1, FK, FE) were evaluated in the presented work.

The roasting process was performed by a home roaster called IRoast2 (Hearthware, Inc., U.S.A.) supported by Café Frei. During roasting three phases were applied and programmed in the roaster. The first phase was held for 1.5 min at 180°C, the second for 2 min at 200°C and the third at 200°C for 3.2, 3.8, 4, 5, 6, 7 min for L1, L2, L3, D1, D2, D3, respectively. The coffee samples were ground for the same particle size (Table 1).

Table 1. Codes of differently roasted, 100% Arabica coffee samples, roasting time of the own roasted samples in the third phase and methods applied on the samples.

	Codes of Arabica coffee samples	Own roasted or commercial sample	Roasting time in the 3rd phase, min	Dr. Lange colour reflectance measurement	Vision system	Electronic tongue	Sensory analysis
1.	L1	Own roasted	3.2	☑	☑	☑	☑
2.	L2	Own roasted	3.8	☑	☑	☑	☑
3.	L3	Own roasted	4	☑	☑	☑	☑
4.	D1	Own roasted	5	☑	☑	☑	☑
5.	D2	Own roasted	6	☑	☑	☑	☑
6.	D3	Own roasted	7	☑	☑	☑	-
7.	B1	Commercial	-	☑	☑	☑	-
8.	B2	Commercial	-	☑	☑	☑	-
9.	T1	Commercial	-	☑	☑	☑	☑
10.	FK	Commercial	-	☑	☑	☑	☑
11.	FE	Commercial	-	☑	☑	☑	-

Seven admixtures were prepared from 100% soft Robusta coffee (RK) by adding 100% ground roasted barley (basic component of cereal coffee, 100+/-5 dimensionless colour value measured by Dr. Lange and 50-60 min roasting time) in different ratio to examine the detectability of impurities in coffee. Barley was added to Robusta coffee in 0-80 w/w%, samples were coded based on their Robusta content (Table 2). Commercially available cereal coffees coded as AF (47% w/w RK- 53% w/w B) and OT (51% w/w RK- 49% w/w B) and the 100% soft Robusta (100RK) samples were also included to measurement. Each sample weighted 18g.

Table 2. Codes of ground roasted Robusta (type K) - barley mixtures and of commercial cereal coffees, their barley content and methods applied on the samples.

	Sample codes	Barley content, w/w%	Own prepared mixture or commercial sample	Vision system	Electronic tongue	Sensory analysis
1.	100RK	0	Own prepared mix	☑	☑	☑
2.	99RK	1	Own prepared mix	☑	☑	☑
3.	95RK	5	Own prepared mix	☑	☑	☑
4.	90RK	10	Own prepared mix	☑	☑	-
5.	80RK	20	Own prepared mix	☑	☑	☑
6.	50RK	50	Own prepared mix	☑	☑	☑
7.	20RK	80	Own prepared mix	☑	☑	-
8.	AF	53	Commercial	☑	☑	☑
9.	OT	49	Commercial	☑	☑	☑

According to the labelling of commercial cereal coffee samples the amount of barley was 49% and 53% in OT and AF, respectively.

Two different types of commercial 100% Robusta coffee (indicated with K-previously applied, and P-only Vietnamese Robusta), a 100% ground roasted barley (B) and two commercial cereal coffees with known Robusta-barley ratios (AF and OT) were measured to determine the effect of coffee type. Table 3 shows the prepared 24 admixtures with different amount of barley in the two different Robusta coffee samples. Each sample weighted 18g.

Table 3. Codes of different coffee-barley mixtures prepared from ground roasted Robusta coffee (type K or P) and of commercial cereal coffee samples, barley content and the applied methods.

	Codes of ground roasted coffee-barley mixtures	Own prepared mixtures or commercial sample	Barley content, w/w%	Vision system (LED and halogen lighting)
1.	100RK	Own prepared	0	☑
2.	99RK	Own prepared	1	☑
3.	95RK	Own prepared	5	☑
4.	90RK	Own prepared	10	☑
5.	85RK	Own prepared	15	☑
6.	80RK	Own prepared	20	☑
7.	75RK	Own prepared	25	☑
8.	70RK	Own prepared	30	☑
9.	65RK	Own prepared	35	☑
10.	60RK	Own prepared	40	☑
11.	55RK	Own prepared	45	☑
12.	50RK	Own prepared	50	☑
13.	100RP	Own prepared	0	☑
14.	99RP	Own prepared	1	☑
15.	95RP	Own prepared	5	☑
16.	90RP	Own prepared	10	☑
17.	85RP	Own prepared	15	☑
18.	80RP	Own prepared	20	☑
19.	75RP	Own prepared	25	☑
20.	70RP	Own prepared	30	☑
21.	65RP	Own prepared	35	☑
22.	60RP	Own prepared	40	☑
23.	55RP	Own prepared	45	☑
24.	50RP	Own prepared	50	☑
25.	AF	Commercial	53	☑
26.	OT	Commercial	49	☑

3.2. Methods

Dr. Lange

Dr. Lange Colour Reflectance Meter Model LK-100 having a built in filter of 640 nm (Dr. Lange GmbH, Dusseldorf, Germany) was applied as a reference method to determine the colour of the ground roasted coffees. The instrument is generally used in the coffee industry.

The measurement was made on the ground roasted samples; there were no other sample preparation. Three parallel assessments were performed on each sample. The value measured by the device is dimensionless, lighter coffees result higher values.

One-way ANOVA, and in case of significant differences Tukey-test was applied for data analysis (Naes et al., 2010).

Vision system

The applied vision system was composed of a Hitachi HV-C20 3CCD camera with Canon TV Zoom lens. Image size was 768×576 pixel, and the optical resolution was 0.0833mm/pixel. The diffuse light was provided by special geometrical settings of 12 halogen lamps (20W each, colour temperature: 3200K). For the experiment the sample was put in a circular, opened at the top, metal sample holder; the same quantity and uniform distribution of the sample was provided with the help of a ruler. After having the image, the sample was put back in its container and was mixed with the rest of the same sample for the next measurement. 10 repetitions of each sample were accomplished.

Images were stored in bitmap format (24 bit/pixel). RGB colour parameters of each pixel of the image made by the camera were transformed into the HSI colour system using the equations of Gonzalez and Woods (1992). Hue is defined as the angular location (0 to 360°) of the colour in HSI colour system. Saturation values were collected into histogram according to the hue angle (sum of saturation). During the evaluation black and white components are not included because they do not contain colour, in this way there is no need for segmentation algorithms contrary to other image processing techniques.

Statistical evaluation of vision system measurement data was realized with the help of the software R 3.0.2 (R Foundation for Statistical Computing, Vienna, Austria). Data evaluation was accomplished by Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Polar Quality System (PQS), Partial Least Squares regression (PLSR) and Support Vector Machine (SVM) methods.

In case of multivariate data evaluation methods, six typical hue values showing the closest correlation with the attribute of interest (Dr. Lange dimensionless value for characterizing the roasting degree, amount of barley in barley-coffee mixture) were selected out of the 360.

The entire hue spectra were taken into account during PQS data reduction method and all the three approaches (point, line and area method) were applied (Kaffka and Seregély, 2002). A new variable, "dominant hue" was introduced for the characterization of the quality points based on the best approach. Dominant hue is defined as the angle between the baseline and vector linking the origin and the quality point (Figure 1). Dominant hue was applied to describe the strength and the nature of the relationship between the examined attributes (roasting degree, barley content).

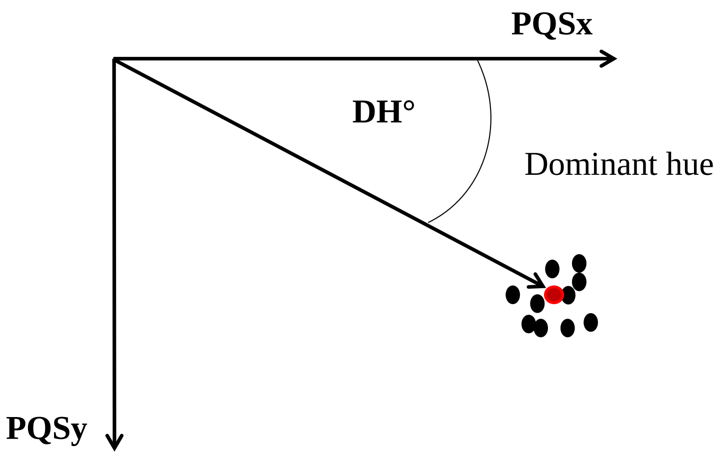

Figure 1 Dominant hue: the angle between the baseline and vector linking the origin and the quality point

<u>Self-developed vision system</u>

Based on the results of the experiments, with my colleague, Lajos Dénes Dénes, we developed a portable vision system with a sample holder and IP camera (Samsung SNB-5001 CMOS sensor). For camera selection it was important the manual settings of the camera parameters (white balance, sharpness) because this is essential to carry out reproducible measurements. A small focal-length lens (Fujian China TV Lens GDS-35 f=35mm 1:1.7) for the digital camera was purchased. Halogen lighting was replaced by LED lighting because it provides the same brightness at a lower power than halogen bulb, thus there is no warming.

The diffuse light was provided by special geometrical settings of six SMD (Surface Mounted Device) LED panels (5.4W, colour temperature: 5600K). The evaluation of the images was the same as previously described.

Sensory analysis

The sensory assessment was performed by 20 untrained panellists. Six coffee samples (Table 1) were evaluated compared to a reference sample during the sensory evaluation based on the ranking test ISO 8587: 2006. The reference sample was previously assessed by a coffee expert. The panellists had to indicate the position of the samples with respect to the attributes on an unstructured scale (14 cm). The attributes for the description were as follows: global aroma, acidic taste, bitter taste, roasted taste, coffee taste intensity and also the preference (not assessed previously).

In the sensory test which reveal the detectability of impurities (ground roasted barley) in coffee 62 students were involved, the majority of them drinks coffee regularly. The assessment was based on a visual inspection of the samples applying the ranking test method. Ground roasted coffee samples were placed in round and white sample holder. Each sample had a three-digit code. Visual inspection method was applied to analyse the intensity and the uniformity of brown colour, the uniformity of particle size and the presence of impurities in each sample. The reference sample was 100RK (100% Robusta coffee) without impurities characterized previously as the most intensive and uniform brown colour and uniform particle size. Panellists had to indicate on an unstructured scale how they percept the six different samples compared to the reference one. The results were obtained in %.

The sensory data evaluation consisted of one-way ANOVA and Tukey-test (Naes et al., 2010). The ANOVA was applied to detect whether panellists found significant differences between the samples according to the given attributes or not. In case of significant differences the Tukey-test was used to find out between which coffees were found the differences.

Electronic tongue

The electronic tongue measurements were performed by an Alpha Astree Electronic Tongue (Alpha M.O.S., Toulouse, France). The device is composed of seven ion-selective sensors (ISFET) with organic coatings and a reference electrode (Ag/AgCl). Coffee samples were prepared according to the industrial practice with 6g of coffees in 100 ml distilled water using pouring procedure, they were filtered and 10-fold diluted for the experiment. Before the measurement the electronic tongue was conditioned with 0.01M HCl solution (AlphaM.O.S., 2003). The calibration was performed by the mixture of the coffee samples. Each sample was measured nine times, between each measurement a cleaning procedure of the sensors was performed in distilled water. In the sequence the order of the samples was randomized. The steady state of the electronic tongue sensor signals was applied as variables for the statistical evaluation considering an average value calculated from the last 10 seconds of each measurement result.

The obtained matrix contained the different sample groups with their repetitions as cases with the seven electronic tongue sensors as variables. The first step of the data processing was the outlier detection based on the results of principal component analysis (PCA). PCA was used for data evaluation as well. Partial least square regression (PLSR) was applied to predict the colour values/roasting degree of the differently roasted coffee samples based on the electronic tongue results and to determine relationship between the results of sensory evaluation and electronic tongue tests. The obtained models were evaluated according to their determination coefficient and root means squared error of cross validation (RMSECV).

For reduction of multivariate sensor data the evaluation included Principal Component Analysis, Linear Discriminant Analysis and Partial Least Squares regression methods (LOO cross-validation) after outlier detection and sensor selection.

4. *Results*

4.1. Evaluation of the effect of roasting time on the colour and taste of differently roasted Arabica coffee

Dr. Lange

Figure 2 indicates the different dimensionless colour values (objective, used in the industry) with mean and standard deviation of every differently roasted own prepared and commercial Arabica coffee samples by the Dr. Lange colour reflectance meter.

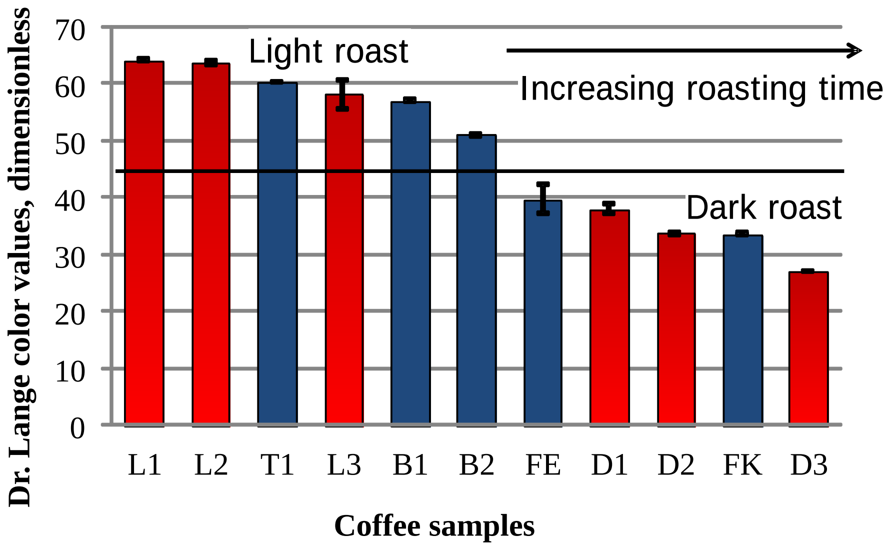

Figure 2. Dimensionless colour values of differently roasted own prepared (red) and commercial (blue) ground Arabica coffee samples (for every samples the means of three parallel measurement and +/- 2σ)

Based on the ANOVA results there are significant differences between the samples by the Dr. Lange colour value ($p<0.01$). Tukey-test showed that only L1-L2 samples and D2-FK samples are not significantly different from each other.

Vision system (halogen lighting)

Differently roasted, own prepared Arabica coffee beans samples were different based on PCA and LDA results (Figure 3). Commercial samples are fitted well in this roasting pattern according to the Dr. Lange colour value.

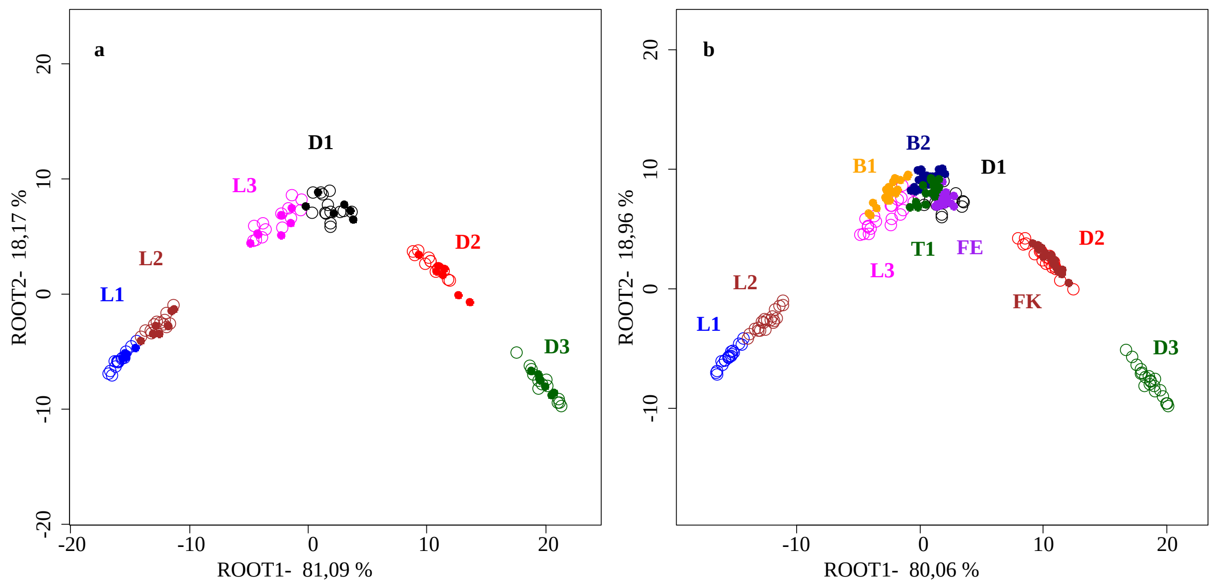

Figure 3. LDA of (**a**) different, own roasted Arabica bean samples (Root1-Root2, n=120, empty dots-calibration (2/3), filled dots- validation (1/3)) and (**b**) of commercial Arabica bean samples projected onto the established model (Root1-Root2, n=220, empty dots-calibration (all of the own roasted samples), filled dots- validation (all of the commercial samples)) based on vision system data

Close correlation was found by PLS regression for the prediction of Dr. Lange colour value based on the established model for own roasted coffee beans (R^2=0.9151, RMSECV= 11.8%). In case of the evaluation of the whole vision system data (without selecting typical hue values) the samples were discriminated in the order of suitable roasting degree, following a monotonous change.

Dominant hue values were compared to Dr. Lange dimensionless colour values in case of own roasted coffee beans. By analysing the correlation the model can be divided into three phases. Generally it is difficult to model the roasting process because it has got phases with different slope (sudden change, slowing down process), therefore the relationship was characterized by the combination of a linear model and an s-model. A complex, sigmoid-like model was established which has got a great practical importance beside its theoretical importance. During roasting in the first minutes only surface colouration can be observed, then starts up the whole bean roast with chemical reactions that is why there is an inflection in the model between the dark and light roasted sample groups.

Roasting degree of coffee bean can be approached with a sigmoid-like curve on an interval important for the practice described by Eq. 1 where φ is the dominant hue, $\varphi_{inflection}$ inflection point of light to dark roast, a, b, c and d are model parameters.

Eq. 1.

$$Dr.\,Lange\ color\ value = \frac{a}{1+e^{\frac{-\varphi+\varphi_{inflection}}{b}}} + c\cdot\varphi + d$$

The fitted sigmoid-like curve on differently roasted samples can be seen at Figure 4. Fitted model's determination coefficient was 0.9689, and validity range: 27.03≤Dr. Lange colour value≤64.15.

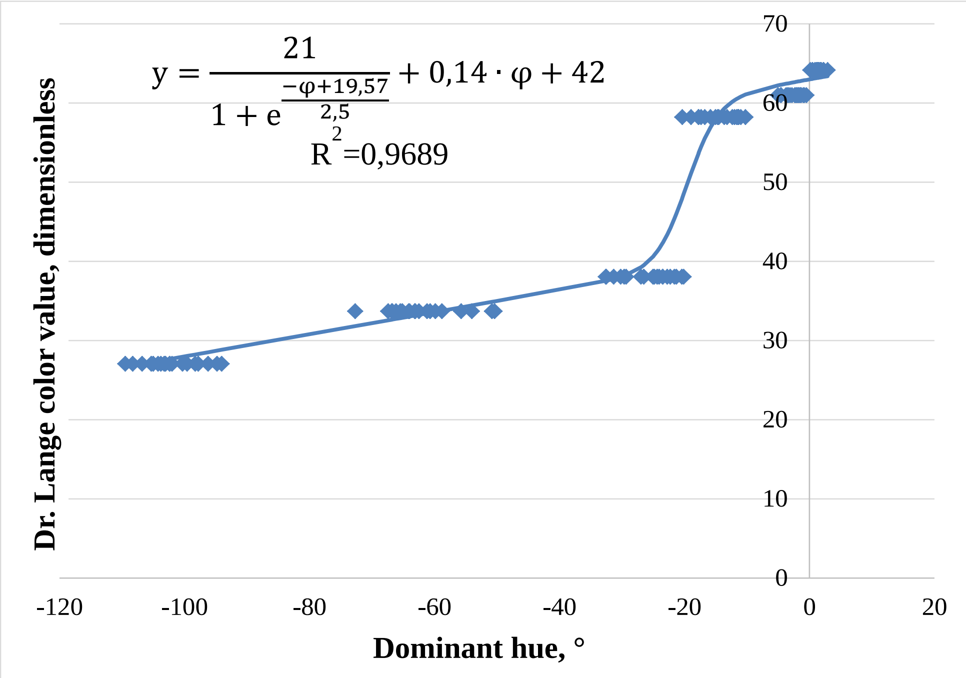

Figure 4. Relationship between dominant hue characterised by PQS line approach and Dr. Lange colour value in case of own roasted Arabica coffee bean samples (validity range: 27.03≤Dr. Lange colour value≤64.15)

On dominant hue values of coffee having given type and roast degree a sigmoid-like model can be fitted that is able to model Dr. Lange colour value characterizing ground roasted coffee colour, without grinding the coffee.

Based on the results of differently roasted Arabica coffee beans and ground coffee assessment I recognized that in most cases the results of coffee samples examined by vision system are following the already established roasting degree trend measured in ground form by Dr. Lange colour reflectance meter. In case of ground coffee assessment vision system results are comparable with the results of colour measurement because the examined sample was the ground roasted coffee in both cases.

The two lightest roast coffee samples are not significantly different from each other, between the darker roast coffee sample groups the difference is increasing according to roasting time.

New scientific result is the finding that relationship between dominant hue and Dr. Lange colour value of roasted coffee can be characterized by a sigmoid-like curve. It makes possible to predict the important technical parameters for the practice (e.g.: inflection point of light to dark roast) already from coffee beans without grinding the coffee. Vision system can be a lower cost alternative for industrial practice.

A suitable sigmoid-like model was found for roasting degree prediction of coffee beans and ground coffee.

Sensory analysis

Panellists found significant differences ($p<0.05$) between analysed coffee samples in global aroma, acidic, bitter and roasted flavour intensity.

Electronic tongue

Light and dark roasted coffee sample groups were discriminated based on the electronic tongue measurement results of own roasted and commercial coffee samples. From the results of electronic tongue assessment the roasting degree can be determined which was characterized by Dr. Lange dimensionless colour values for the comparison of the two methods. According to the parameters of PLS regression prediction of roasting degree was realized by close correlation and low error ($R^2= 0.99$, RMSECV= 3.24%). Prediction of Dr. Lange dimensionless colour value of commercial sample was weaker with higher error.

Among the attributes assessed by sensory analysis roasted flavour intensity was the best predictable ($R^2=0.90$) from electronic tongue data. It was followed by acidic ($R^2=0.82$) and coffee ($R^2=0.81$) taste intensity that we found in a previous research as well.

4.2. Detection of the presence of ground roasted barley as impurity mixed to Robusta coffee

Vision system

Groups of Robusta-barley mixtures with low barley content (0-10w/w%) are overlapping according to vision system measurement results (Figure 5). With increasing barley content there is a higher difference between the coffee sample groups.

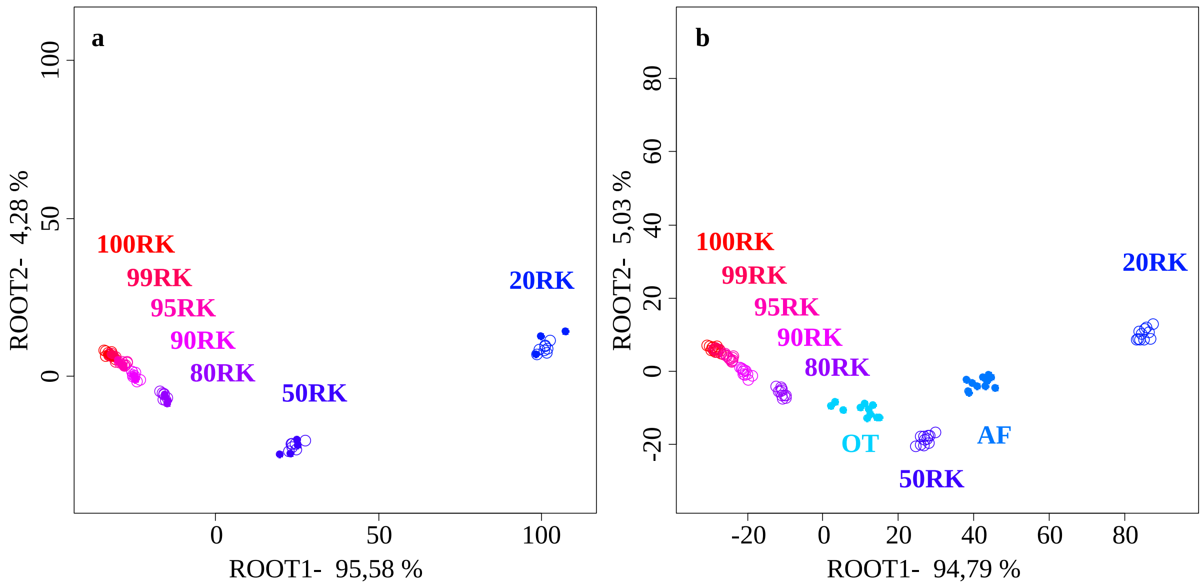

Figure 5. LDA of (**a**) Robusta (type K) -barley mixtures (Root1-Root2, n=70, empty dots-calibration (2/3), filled dots- validation (1/3)) and (**b**) of commercial cereal coffee samples projected onto the established model (Root1-Root2, n=90, empty dots-calibration (all of the own prepared samples), filled dots- validation (all of the commercial samples: AF, OT) based on vision system data

According to the six selected hue value the prediction (PLSR) of barley content was realized by close correlation (R^2=0.9985) and low error (RMSECV=1.33%).

A close, linear relationship was found between barley content and dominant hue (established previously based on PQS method) (R^2=0.9955) (Figure 6).

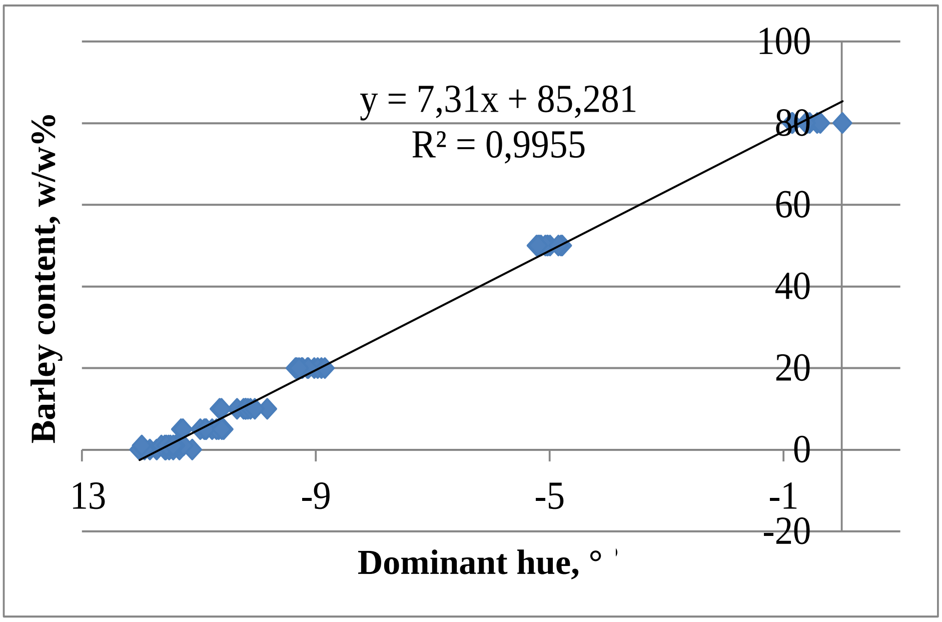

Figure 6. Relationship between dominant hue and barley content of own prepared Robusta-barley mixtures (halogen lighting)

Results of image processing found in the literature showed that the concentration of impurities is predictable with lower, 5w/w% accuracy, correlation (R=0.9-0.99) was similarly close (Delgado Assad et al., 2002; Sano et al., 2003). It was proven by a measurement that by image processing of vision system data barley content of Robusta-barley mixtures is well predictable.

Sensory analysis

Based on the sensory analysis (visual inspection) panellists could not rank the samples in right barley content order. Panellists' opinion was that if there is no reference sample they cannot recognize whether the examined sample contains barley or not.

Electronic tongue

According to the electronic tongue results in case of low barley content (0-10w/w%) samples are not differentiated from each other. Coffee drinks' difference grows with higher barley content. With the help of PLS regression model the smallest barley content that is considered as significantly ($p>0.05$) higher than 0w/w% by electronic tongue was determined. Thus the determined detection threshold at the given model besides the discrete measured values was 10w/w%.

4.3. Fraudulent barley detection in two different types of Robusta coffee for the evaluation of the effect of coffee type

Samples composed of barley added in different ratios to two different type of Robusta coffee were successfully discriminated by growing barley content according to vision system data with both lighting type (LED and halogen) (Figure 7). Based on LED lighting vision system results the effect of barley content is higher that the effect of Robusta coffee type. It means that the measurement is independent of Robusta coffee type; the results are referred to the added barley amount differences.

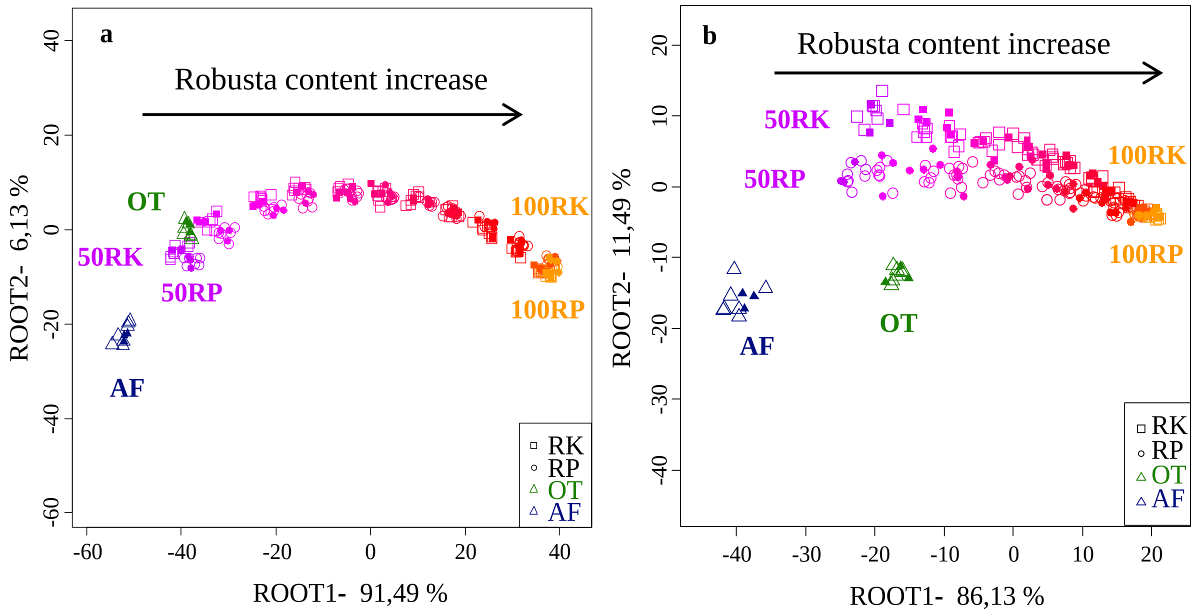

Figure 7. LDA of barley added in different amount to two different types of Robusta (K, P) coffee samples based on vision system data using (**a**) LED lighting and (**b**) halogen lighting (Root1-Root2, n=250, classification variable: composition in w/w% and coffee type)

Among the three approaches of PQS data reduction technique point method was found to be suitable in case of LED lighting. The represented points of coffee samples showed a monotonous change along a linear path in the right order of Robusta ratio (Figure 8). The relationship was characterized by close correlation (R^2=0.9864). The built linear model was independent of Robusta type.

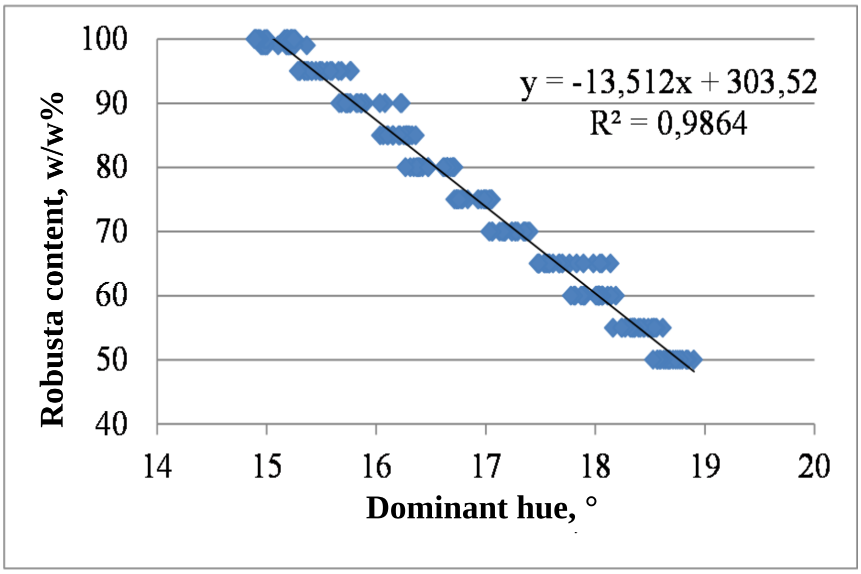

Figure 8. Relationship between dominant hue and Robusta content of own prepared Robusta-barley mixtures (LED lighting)

According to the model the prediction of Robusta content was realized by a difference lower than 5w/w% compared to the uncertain labelling of commercial cereal coffee (RMSEP=4.98w/w%). PLS regression realized by six typical hue value resulted a model loaded with systematic error. Prediction error of the relationship obtained by radial SVM method was 2w/w%.

Differences were observed according to increasing Robusta content between samples in case of halogen lighting however the groups were overlapped. The effect of Robusta type was also important besides the amount of mixed barley.

New scientific results (Theses)

New scientific results are proven completely for the given devices and measured samples, however I think that the established measuring methods and data evaluation algorithms can be extended to other potential impurities. The fact that there were no studies concerning the detection of possible impurities in coffee by the electronic tongue based on the literature and this question was not subject of investigation of any sensory analysis improves the importance of my work.

1. New measuring and data evaluation method based on computer vision system was developed to monitor the roasting process of coffee, and to determine the amount of barley mixed to coffee. It was proven with the evaluation (multivariate method: PCA, LDA) of data that the spectra-like data set resulted by the sum of saturation values related to a given hue value is suitable to monotone following the colour changes during roasting and that caused by the mixed barley in different amount to coffee.
2. A new variable, “dominant hue” was introduced to characterize the colour changes of Arabica coffee during roasting. It was found that using the dominant hue, Dr. Lange colour value of roasted coffee can be predicted with close correlation (R^2=0.9689) without grinding the coffee. The relationship can be characterized by a sigmoid-like curve which makes possible to predict the technical parameters important for the practice (e.g.: inflection point of light to dark roast). It was proven by measurements that dominant hue is applicable to characterize Robusta-barley mixtures with changing ratio, the relationship can be describe with linear model (R^2=0.9955).
3. It was found that the electronic tongue is able to monitor monotonously the chemical changes occurring during roasting, strong differences were detected between light and dark roasted Arabica coffee samples. Panellists involved in the sensory analysis detected significant differences for roasted taste intensity attribute between light and dark roasted sample groups. Among the sensory attributes predicted from electronic tongue data roasted taste intensity attribute was the best predictable (R^2=0.90).
4. It was determined that based on electronic tongue results the amount of barley in Robusta coffee-barley mixtures is predictable with close correlation (R^2=0.9506, RMSECV=7.6w/w%). Detection threshold at the given model besides the discrete measured values was 10w/w%.

5. New image processing device was developed (with LED lighting) to detect the amount of barley mixed to Robusta coffee. It was demonstrated that there is a strong linear relationship between the dominant hue values calculated from the measured data of the developed device and the barley content of the samples (R^2=0.9864).
6. With measurements it was proven that the samples composed of barley added to two different type of Robusta coffee in different ratio can be differentiated based on vision system method with both (halogen and LED) lighting. The effect of the amount of barley in Robusta coffee-barley mixtures was found stronger than that of the type of Robusta coffee, thus the result of the colour measurement is independent of the Robusta coffee type.

Conclusions and suggestions

The results of my research establish the basis of a vision system equipped with a sample holder, able to monitor online the roasting process, installed in the roasting machine can help to stop the process in the right time.

For that purpose in every cases a smaller amount of batch should be roasted before in a small manual roaster to receive the roasting profile of the given sample. Images about the batch have to be continuously taken and the data has to be processed with the help of the algorithm established in my work. The received colour parameters should be inserted in the data evaluating unit built in the vision system connected to the industrial roaster.

In the industrial roaster with same conditions as the manual roaster we prepare images that will be compared continuously to the previously established model parameters and the end of the roasting process will get visible.

To introduce this instrument in practice many measurements are required in industrial conditions, however the results of my research and the developed device mean the basis of the application of such equipment.

The special device with LED lighting developed during my research is also suitable for detection of barley mixed to coffee. Based on dominant hue method obtained from PQS results it was possible to quantify the amount of barley. For further analysis it would be worth to extend the method for other possible impurities and to prepare a portable device which is able to help the work of the authorities during control as a fast method.

Publications related to the topic

Articles with impact factor

E Várvölgyi, A Gere, D Szöllősi, L Sipos, Z Kovács, Z Kókai, M Csóka, Zs Mednyánszky, A Fekete, K Korány (2015) Application of sensory assessment, electronic tongue and GC-MS to characterize coffee samples. Arabian Journal for Science and Engineering 40:(1) pp. 125-133. (IF. 2013: 0,367)

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