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Sensor Fusion for Maturity Prediction of Pepper

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In order to improve the determination of pepper maturity, we examined a fusion of non-destructive sensor outputs and a fusion of destructive reference parameters. Multi-sensor models were assessed against single sensor models based on the significantly lower root mean square errors of cross validation values for all tested cultivars and all reference parameters. The fusion procedure was based on the combination of sensor outputs and the combination of reference parameters. Linear and non-linear regression methods were applied for model establishment.
Through the reference parameter fusion a new combined quality index was developed in order to assess the global quality of the produce. With this new combined quality index, the comprehensive quality of the produce could be predicted as well as its maturity stage. This could support better decisions regarding harvest schedule; as the new index correlate with physical property change during growth.
The sensors used in the present work were spectrophotometers at the VIS-NIR and SWIR spectral range, relaxation and ultrasonic tests, and colour measurement. The reference parameters were the following: total soluble solids, dry matter, osmotic potential, ascorbic acid, total chlorophylls, carotenoids content, coefficient of elasticity measured in compression and rupture mode.

1. Introduction

Quality measurement of fresh produce is a combination of different features including visual appearance, nutritional value and flavour. Many of these features are determined either by human or through different vision systems, destructive, non-destructive methods or chemical analysis (Kader, 2002). For this practice, if the procedure of quality determination is mechanical, samples are distinguished based on one or a few single attributes, such as colour, total soluble solid content or texture. This type of sample differentiation draws conclusion on the produce quality based on limited information. The drawback of human classification of produce based on its quality is slow, time consuming and its repeatability is low (Steinmetz et al., 1999b). The sensor-based simulation of such a complex sensation is a challenging task. The fusion methodology suggested by Steinmetz et al. (1999b) is a process containing eight steps, containing the system assessment and possibilities for its improvement. Table 1 presents a short overview of research works which were conducted in the recent years in the field of agriculture, focusing on the quality prediction of fruits and vegetables. As mentioned in the overview, there are no standard rules in making fusion. While conducting fusion, a wide range of sensors are used online or in the training set with wide spectrum of statistical regression, classification methods and learning machines in order to predict the quality of the produce. For each case it was concluded that sensor fusion yielded a considerably (5-20 %) lower error of regression or classification. This fact encourages the continuation of sensor fusion research to be used in wider produce range and as well as a possible tool in the complex quality prediction. This work presents a study of sensor fusion for the quality detection of bell peppers and a novel approach of quality attributes merging, resulting in a new combined quality index.

Table 1: Overviews of prediction of quality parameters by fusion

Agricultural product	Predicted component	DT Method	NDT Method	Statistical Method	Reference
apple	firmness, soluble solids content (SSC)	Magness-Taylor, digital refractometer	Acoustic firmness sensor, Bioyield tester, VIS/SWIR, Online hyperspectral scattering	PLS	Mendoza et al., 2012
pepper	shrinkage, firmness, colour	Texture Analyzer	Weight, Image acquisition	ANN	Mohebbi et al., 2011
pepper	DW, TSS	Conventional method, Refractometer	Ultrasonic, relaxation, colour	PCR	Ignat et al., 2010
tomato	colour, firmness		Colorimeter, impact and acoustic test	Bayesian classifier	Baltazar et al., 2008
apple	firmness, soluble solids content (SSC)		Acoustic impulse resonance frequency sensor, VIS/NIR	PLS, PLSDA	Zude et al., 2006
eggplant	colour, length, girth, bruises		Image processing	ANN	Saito et al., 2003
peach	Firmness, SSC, Acidity, chlorophyll, carotenoids, anthocyans	Penetrometer, refractometer, Laboratory measurement	MMS1-NIR, electronic nose	PLS, PLSDA	Natale et al., 2002
apple	sugar	Refractometer	Vision system, NIR	MNN	Steinmetz et al., 1999a
orange	size, weight, firmness, TSS, acidity, colour	Refractometer, Titration	Vision system, Impact firmness sensor, NIR, Colorimeter	PCA, MLR, FDA, NN	Steinmetz et al., 1997

2. Materials and methods

2.1 Plant materials

The experiments were carried out in three commercial greenhouses with cultivars: 'Ever Green' (green variety), 'No. 117' (yellow variety), and 'Celica' (red variety). The pepper samples chosen for the study were marked during their flowering stage and fruits were picked nine times along the growing season: at 1 week intervals during the 9-week growing period from the 34th day after anthesis (DAA) until full ripening (88th DAA), and when fully grown. Each picked batch of each cultivar comprised 20 fruits, i.e., a total of 180 fruits of each cultivar. Shortly after picking, the fruits were cooled and kept in an air-conditioned laboratory at 23°C. Firstly, the fruits were subjected to spectral measurements through scanning at the half-length of one side of each pepper. Samples were then taken from the same location, for the destructive determination of chlorophylls and carotenoids content.

2.2 Non-destructive measurements

Shortly after picking, the colour of pepper the fruit was measured by a colorimeter (Minolta Data Processor DP-301, Chroma Meter CR-300). Spectral reflectance of pepper fruit was measured through a USB2000 (Ocean Optics, Dunedin, FL, USA) mini spectrometer, with spectral range: 350-1000 nm. The light source was LS-1 Tungsten Halogen Light (Ocean Optics, Dunedin, FL, USA). Further spectral measurements were obtained using a Liga SWIR spectrophotometer (STEAG Micro Parts, Dortmund, Germany) with the same light source. Both configurations were calibrated with a Spectralon, WS-1-SL standard white ceramic background disc (Ocean Optics, Dunedin, FL, USA). The spectral measurement systems were arranged in diffused reflectance mode to receive the signals from the peel and flesh of the fruit. The spectrophotometers sampled an area on the circumference of the largest cross-section, perpendicular to the stem-blossom axis. The sampled area of each fruit was scanned 10 times, and the readings were automatically averaged to form a single spectrum signal.

A high-power, low-frequency ultrasonic pulse generator-receiver (Krautkramer Model USL33) and a pair of 50 kHz ultrasonic transducers were used to generate the signal coupled to a microcomputer system for data acquisition and analysis. The ultrasonic measurements were conducted with the measurement system established by Mizrach (1999) on a relatively flat area on the pepper fruit. The attenuation of the ultrasonic signal was calculated according to the equation of Krautkramer and Krautkramer (1990).

Relaxation test was chosen to follow non-destructively the changes in firmness of the pepper samples during growth and development. Relaxation test has revealed strong correlation in preliminary experiments with the generally adapted pressure gage method measuring firmness of the entire bell pepper fruit (Meir et al., 1995).

General purpose relaxation test was conducted with Lloyd LR SK Instrument (Lloyd Instruments Ltd., UK).The intact fruit was laid on its side on a flat plate and was compressed using a moving plate with the speed of 200 mm/min until reaching 20 N loads; hold time was 10 second. The rate of relaxation was expressed in N/s, and the remaining deformation in mm; additionally, the coefficient of elasticity ($CE_{Relaxation}$, N/mm) was calculated from the loading phase.
Samples of for all destructive reference measurements were taken from the pericarp location at which NDT measurements had been performed.

2.3 Destructive measurements
Compress to Rupture Test was carried out with Lloyd LR SK Instrument (Lloyd Instruments Ltd., UK). A 3 cm by 3 cm test strip was cut from the pepper fruit. Each sample was characterized by the coefficient of elasticity ($CE_{Rupture}$, N/mm) calculated from the section before the proportionality limit (Bourne, 1982).
Compress to Limit Test was carried out with Lloyd LR SK Instrument (Lloyd InstrumentsLtd., UK).A test disk of 15 mm diameter was cut from the pepper. The disk was placed on the centre of the flat plate with its peel down. The speed of the upper plate was 100 mm/min. The upper plate was compressing the sample until a certain point when the distance between the probe and the lower plate was 1 mm. Each fruit was characterized by two calculated parameters: the coefficient of elasticity ($CE_{Compression}$, N/mm), calculated from the section of the load-deformation curve before the proportionality limit (Bourne, 1982), and the integral of the load-deformation curve ($Int_{Compression}$). The integral was calculated from the start of deformation until the proportionality limit.
Determination of dry matter (DM) was carried out at 60□C in a forced-air oven for 72 h. Total soluble solids content (TSS) was measured using a digital refractometer (Atago, PR-1). TSS was expressed in Brix %.The determination of ascorbic acid (AA) content was carried out based on the official method (AOAC, 2000). Total chlorophylls and carotenoids contents were determined through extraction in absolute ethanol, and the measurement of optical absorbance at 470-, 648.6-, and 664.2 nm. The total chlorophylls and carotenoids contents were determined according to the equations established by Lichtenthaler (1987). The measurement of osmotic potential (OP) was carried out by cryoscopic micro-osmometer (µOsmette, Precision Systems, Natick, MA, USA). Results of OP are expressed in mOsm (kg H2O)$^{-1}$.

2.4 Analysis
Two indices were calculated from the spectral measurements: the spectral angle mapper index - SAM (Park et al., 2007) and the quality point of the spectrum (PQS, D) (Kaffka and Gyarmati, 1991).
Linear and non-linear regression methods were used to develop the models: Partial least squares regression (PLSR), Principal component regression (PLS, Eigenvector Research, Wenatchee, WA, USA), Support Vector Machine (SVM), a supervised learning algorithm, and a Kernel algorithm based on the Bayesian theorem (Lee, 2004, Gelman et al., 2004, Fearn et al., 2010), developed by Ignat et al. (2013). All regression methods were run under Matlab software R2012a (MathWorks, Natick, MA, USA).
Residual predictive deviation (RPD) index was determined, to evaluate the goodness of the models; it is calculated as the ratio of performance to deviation (Fearn, 2002). Along with the RPD, a standardized weighted sum index (SWS) was calculated to compare the performance between the models (Ignat et al., 2012).
In the present work, the fusion methodology suggested by Steinmetz et al. (1999b) was applied:

a. To identify the properties of the produce those are important for its organoleptic properties: internal content, colour, texture.
b. To identify the reference methods (qualitative or quantitative) currently applied to assess the quality of the produce: TSS, DM, AA, OP, total chlorophylls, carotenoids, texture (CECompression, CERupture).
c. To identify the non-destructive methods that can be applied to measure the selected properties of the produce: relaxation test, ultrasound, VIS-NIR and SWIR spectral measurements.
d. To acquire data on the produce with the selected non-destructive sensors and reference methods: measurements during growing and maturation.
e. To assess the level of redundancy or complementarity in the non-destructive sensors: PLS models.
f. To select and apply the proper multi-sensor fusion method: PLS, PCR, Kernel, SVM.
g. To evaluate the developed sensor fusion system by comparing its performance with the reference methods: SWS.
h. Acceptance, rejection or improvement of the proposed sensor fusion method.

Model evaluation was conducted by comparing a single-sensor system with a multi-sensor system, applying the SWS index to assess the performance of single and multi-sensor systems. Performance is defined as the ability of the fusion model to provide the properties of the produce with better predictions than a single sensor. Our study carried out the fusion at three levels: I. Fusion of the NDT data, II. Combination of the cultivars, III. Fusion of the DT parameters

3. Results and discussion

In the first level of fusion the NDT data were fused in order to analyse the effect of data combination to predict the DT quality attributes of bell peppers. As a first step of the fusion different feature extraction methods were applied on the data originated from the different measurement methods: for the VIS-NIR and SWIR data the SAM of the spectra, D, principal components of the PQS (PC1 and PC2) quality point, as well as the first and second LV-s from the best PLSR models were calculated. Ultrasonic attenuation, compression data and colour data were used in their raw format.

Performance measures of PLS regression models were calculated for single-sensor and multi-sensor systems. A single-sensor system refers to the use of VIS-NIR or SWIR spectral measurements; a multi-sensor system refers to the NDT data fusion. By comparing the single sensor and multi sensor models for all three pepper cultivars (Table 2 presents the comparison for the 'Ever Green' cultivar as an example), the fused NDT data provided higher SWS indices to predict each of the DT parameters. Moreover, the models based on the fused data predict the DT parameters with similar or lower number of latent variables (LV); they have generally higher coefficient of determination as well as lower RMSECV (Difference in RMSECV relative to the models based on the fused data - taken as 100% - indicated in the last column of Tables 2 in percentage). Fusion of relaxation, ultrasonic, colour and spectral measurement data can predict inner composition and textural state of different bell pepper cultivars better than each cultivar separately based on the performance measures; despite the alteration in the colour of some pepper varieties during the growth and maturation while other varieties keep their original coloration.

PLS, PCR, Kernel and SVM regression analyses were used to build the models to predict DT parameters with fused NDT data. Table 3 illustrates as an example the AA prediction results for 'Ever Green' cultivar. Overall comparison of the linear and non-linear regression methods based on the SWS index revealed that PLS and SVM regressions were most suitable to predict DT parameters using the fused NDT data.

At the second level of fusion, we expected to verify the possibility of combining the cultivars despite their altered final colour, and build general models to predict each DT parameter. Table 4 presents an example for the result of the PLS, PCR, Kernel and SVM regression models for TSS prediction. An overview of the results indicates that the PCR regression required significantly more PC-s to build the models; in addition, this method generally has higher RMSECV. Therefore, we do not suggest analyses of combined varieties and fused NDT data to assess bell pepper evaluation. For most of the cases, the Kernel and SVM regressions resulted in the most efficient models.

Table 2: Performance measures of PLS regression models for TSS using data from the VIS-NIR, SWIR spectral ranges and fused NDT data. Models for the 'Ever Green' pepper cultivar are presented

DT	NDT	LV	R2	RMSEC	RMSECV	RPD	RMSECV/RMSEC	SWS	Difference in RMSECV
TSS, Brix %	VIS-NIR	3	0.93	0.3	0.4	3.9	1.3	0.71	127%
	SWIR	9	0.91	0.3	0.4	3.3	1.3	0.40	147%
	Fusion of NDT	5	0.96	0.2	0.3	4.9	1.3	0.81	100%

Table 3: Performance measures of PLS, PCR, Kernel and SVM regression models for AA, using NDT fused data. Models for the three pepper varieties are presented: 'Ever Green' cultivar

DT	Cultivar	Regression analysis	LV	R^2	RMSEC	RMSECV	RPD	RMSECV/ RMSEC	SWS
Ascorbic acid, mg/100g	Ever Green	PLS	5	0.83	10.02	13.88	2.3	1.4	0.73
		PCR	9	0.70	15.79	17.22	1.9	1.1	0.41
		Kernel	9	0.82	9.23	18.23	1.7	2.0	0.36
		SVM	5	0.79	9.72	15.00	2.1	1.5	0.85

Table 4: Performance measures of PLS, PCR, Kernel and SVM regression models for DT parameters, using the fused NDT data. Models of the data combination of the three pepper cultivars are presented

DT	Regression analysis	LV	R2	RMSEC	RMSECV	RPD	RMSECV/ RMSEC	SWS
TSS, Brix%	PLS	5	0.93	0.40	0.45	3.8	1.11	0.67
	PCR	4	0.87	0.62	0.64	2.7	1.02	0.36
	Kernel	5	0.93	0.42	0.47	3.6	1.13	0.58
	SVM	5	0.93	0.37	0.43	4.0	1.16	0.67

Based on the comparison of the single and the combined cultivar models it can be concluded that the combined variety models have higher R^2 coefficients and lower ratio of RMSECV to RMSEC, which makes these models more robust suggesting the possibility of application to predict DT parameter.
DT quality parameters fusion was conducted at the 3rd level of fusion. We employed PCA in the fusion of DT parameters, and the 1st PC was taken as a new combined quality index (NCQI). Efficient models were achieved with the fused DT parameters and fused NDT models for all three cultivars with high coefficient of determination. One of the best models is depicted in Figure 1 in scatter plots for 'Ever Green' cultivar. Based on the models built for the prediction of NCQI, it was found that the NCQI has negative values when the pepper fruit is still in the stage of physiological development (before 60th DAA). Before the 60th DAA the pepper fruit did not reach its maximum size and did not accumulate the optimal amount of internal components such as soluble solids, carotenoids or AA. Therefore, harvest is not recommended when the NCQI obtains negative values. PLS and SVM methods proved more suitable to work with the combined cultivar datasets and build regression models for the fused DT and NDT data.
Generally, it is recommended to test the model applicability; therefore, the combined cultivar dataset (540 samples) received a random division into a calibration set (300 samples) and a validation set (240 samples). Both PLS and SVM regressions resulted in excellent models. Based on the calculated SWS indices, the PLS model (Figure 2) proved slightly better than the SVM, with SWS values of 0.81 and 0.71, respectively.

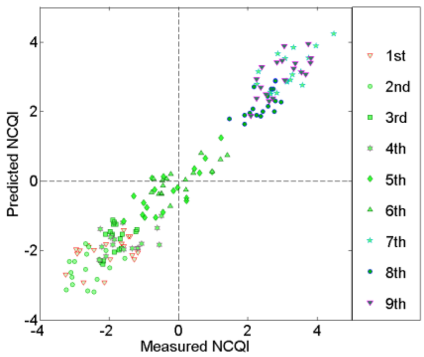

Figure 1: Scatter plot of NCQI, as predicted by PLS regression model (marks: harvest schedule)

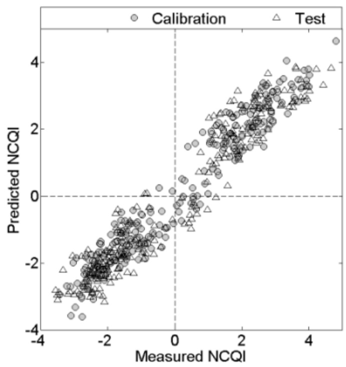

Figure 2: Scatter plot of NCQI, as predicted by PLS regression model

4. Conclusion

In this study, we examined the alterations in the quality attributes measured through destructive and non-destructive methods in the course of growth and maturation of intact bell pepper fruits. The performances of single sensor and multi-sensor models to predict maturity and quality attributes were assessed. We successfully applied linear and non-linear regression models to the fused NDT data of the combination of pepper cultivars datasets to predict DT parameters. Fusion of relaxation, ultrasonic, colour and spectral measurement can predict inner composition and textural state of different bell pepper cultivars better than separately based on the performance measures. A combined quality index (NCQI) was developed through the fusion of reference parameters (DT) establishing an alternative to assess the maturity and global quality of a produce. Regression models were built for the prediction of NCQI using the fused NDT data for a single cultivar, and the combination of the three cultivars. PLS and SVM regressions provided the most satisfactory prediction models. Based on the NCQI prediction results, it was found that the NCQI obtained negative values when the pepper fruit was still at the physiological development; therefore, harvest time is recommended when NCQI start to change from negative values to positive. Researchers should consider further studies with the examination of the NCQI behaviour during storage and shelf life along with sensor selection in order to find the most efficient and economical solution for fusion, which can be integrated into sorting and classification lines.

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