Classification of the firmness of peaches by sensor fusion

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Abstract: The objectives of this research were to compare the performance of each individual nondestructive sensor with the destructive sensor, and to apply sensor fusion technique to explore whether a combination of sensors would give better results than a single sensor for classification of peach firmness. Tests were carried out with four peach varieties namely *Royal Glory*, *Caterina*, *Tirrenia* and *Suidring*. In this research, the three nondestructive firmness sensors acoustic firmness, low-mass impact and micro-deformation impact were used to measure firmness. A Bayesian classifier was chosen to provide a classification into three categories, namely soft, intermediate and hard. High level fusion technique was performed by using identity declaration provided by each sensor. The data fusion system processed the information of the sensors to output the fused data. The result of the high level fusion was compared with the classification provided by an unsupervised algorithm based on destructive reference measurement. The fusion process of the nondestructive sensors provided some improvements in the firmness classification; the error rate varied from 25% to 19% for individual sensor. Furthermore, the results of fusion process by using three sensors decreased the error rate from 19% to 13%. This research demonstrated that the fused systems provided more complete and complementary information and, thus, were more effective than individual sensors in the firmness classification of peaches.

Keywords: peach, firmness classification, nondestructive sensor, high level fusion, Bayesian classifier

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1 Introduction

Firmness is an important textural parameter for the determination of harvest time, fruit maturity, and quality grade[1]. Peach quality is determined by several factors including ground color of the skin, sugar content, firmness, aroma and taste. However, peach quality is most closely related to firmness, as indicated by a Magness-Taylor firmness test. Ground color of the peach skin is commonly accepted as the second indicator of maturity[2,3]. Destructive or nondestructive methods can be used to measure fruit firmness. Traditionally

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Magness-Taylor procedure which is defined as destructive measurement is a classical method and commonly used to measure the firmness of fruit flesh[4,5].

At present, nondestructive or minimally destructive sensors that are potentially useful for rapid, non-destructive prediction of fruit firmness such as acoustic[6-11], micro-deformation[5,12-16], low-mass impact[17-22], ultrasonic[23-29], optical in the NIR or VIS-NIR range[30-37], and hyperspectral and multispectral scattering[38-43] have been used and compared to destructive measurements by many researchers.

It still remains difficult to compare one sensor with another, or to determine the specific advantages of each sensor. Since these sensors work with different principles and each of them has its merits and limitations in measuring specific quality parameters, the fusion of them would provide more detailed and potentially complementary information. Sensor fusion is the process of integration of multiple data and knowledge representing the same real-world object into a consistent, accurate, and useful representation. Sensor fusion is also known as (multi-sensor) data fusion and is a subset of information fusion.

Theoretical developments in sensor fusion have influenced the studies on nondestructive firmness sensing, based on the fact that combinations of sensors should give a better results than each individual sensor alone[2]. Furthermore, sensor fusion approach enables rapid and economical on-line implementation for fruit quality assessment[44]. As mentioned above, several studies examined and compared different excitations such as acoustic, micro-deformation, low-mass impact, optical spectroscopy, hyper spectral and multispectral scattering. In other studies some researchers concentrated on fusion method by combining two or more sensors to improve performance.

Steinmetz et al.[45] used fusion method by combining a vision system and a near-infrared spectrophotometer for on-line, real-time, nondestructive sugar content prediction of “Golden Delicious” apples. They used a multi-layer neural network fusion technique since a strong non-linearity in the relationship between color and sugar content was expected. It was found in their study that the repeatability of the classification of fruits based on sugar content was improved when two sensors were combined. The sensors and the fusion process were implemented on-line within a robotic device running at 3-5 s per fruit. Roussel et al.[46] used Bayesian fusion method by combining aroma, FT-IR and UV sensors for discrimination of white grape varieties. They developed two methods based on Bayesian inference: the Bayesian minimum error fusion rule and the minimum risk rule. A significant improvement in the grape variety discrimination was provided by combining the outputs of each sensor individually. Zakaria et al.[11] work on the classification of mango maturity and ripeness levels using fusion of the data of an electronic nose and an acoustic sensor. Two data fusion techniques such as Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) were used to discriminate the mangoes harvested at week 7 and week 8 based solely on the aroma and volatile gases released from the mangoes. By applying low-level data fusion technique on the e-nose and acoustic data, the classification for maturity and ripeness levels using LDA was improved. However, no significant improvement was observed using PCA with data fusion technique. Mendoza et al.[1] evaluated four sensing systems (acoustic firmness, bio-yield firmness, visible and shortwave near infrared spectroscopy and spectral scattering) and combined for nondestructive prediction of the firmness and soluble solid content of *Jonagold*, *Golden Delicious* and *Red Delicious* apples. Better predictions of the firmness and, in most cases, of the soluble solid content were obtained using sensors fusion than using individual sensor. This research demonstrated that the fused systems provided more complete and complementary information in prediction of apple quality. Baltazar et al.[47] applied data fusion method to nondestructive testing data for classification of fresh intact tomatoes based on their ripening stages. Bayesian classifier considering a multivariate, three-class problem was incorporated for data fusion. Numerical results showed that multi-sensorial data fusion considerably reduced the ripening classification error from 48% (single sensor) to 11% (multi-sensor). Ignat et al.[48] studied the fusion of nondestructive sensor outputs and a fusion of destructive reference parameters. Spectrometers in the VIS-NIR and SWIR spectral range, hyperspectral imaging in the visible range, relaxation and ultrasonic test, and color sensors were used for maturity prediction of intact bell peppers by sensor fusion. Linear and non-linear regression methods were applied for model establishment. Multi-sensor models were found better than single sensor models based on the significantly lower root mean square errors of cross validation values for all tested cultivars and all reference parameters.

Sensors used in our research measured the same property of the peach, i.e. firmness. In order to compare and combine them, they were used on the same peaches and in the same experimental conditions. A collaborative experiment was set up which enabled the comparison and the fusion of three firmness sensors. The objectives of the present work were: (1) to compare the performance of each individual nondestructive sensor to the destructive sensor; (2) to apply sensor fusion technique in order to determine peach firmness; (3) to compare the performance of the fusion process with each individual sensor.

2 Materials and methods

2.1 Plant materials

Four peach varieties "*Royal Glory*" as red soft flesh and ripe, "*Caterian*" as yellow flesh and ripe, "*Tirrenia*" as yellow flesh and unripe and "*Suidring*" as red hard flesh and unripe, were used in the tests during 2011 season for this study. Four tested varieties were supplied from the market in Madrid and were kept in laboratory conditions of about 20°C during the test period. A total of 136 peach fruits (33 peaches for *Royal Glory* and *Caterina*, 43 peaches for *Tirrenia* and 27 peaches for *Suidring*) were considered and selected from the boxes for each variety. Peach samples were selected from the boxes by eyes and touched to make a group with unripe, intermediate ripe and ripe peaches in the same group for each variety. Peaches were tested in every day for 5 days during storage in 20°C room conditions for getting a wide range of firmness stage depending on the variety properties. Samples were tested nondestructively and destructively. After destructive measurement, the number of samples in the group decreased as a result of destructive test nature. For taking the measurements, two sides of peaches, considered to be divided by the suture of the fruit, were differentiated the most colored side (blush) an, and the least colored side (non-blush). Totally, six measurements for each peach were taken from three points within the longitudinal axis of the peach for two sides in each test. The destructive and nondestructive test points on a peach sample are shown in Figure 1.

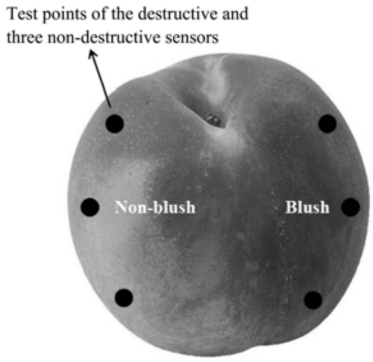


Figure 1 Destructive and nondestructive test points on a peach sample

2.2 Nondestructive sensors and measurements

The experimental set-up included three nondestructive tests and one destructive reference measurement that were designed to detect firmness. Each sample was processed successively through the three individual sensors for nondestructive measurements in the following order:

2.2.1 Acoustic firmness sensor by Aweta

Acoustic firmness measurements were done by using a commercial bench-top unit AFS designed by Aweta (Model DTF Vo.0.0.82, Nootdrop, The Netherlands) (Figure 2). It was used to measure the resonance frequency of peaches. This bench-top sensor first determines the weight of the peach by a small load cell, followed by gently tapping at the fruit[1]. The resulting sound is analyzed and transformed into the frequency domain to obtain the first natural or resonant frequency (f[Hz]). To capture the acoustic vibration waveform, a small microphone was embedded in the flange of this unit. The Aweta acoustic firmness sensor gives two different types of measurements. The firmness index (FI) is based on the acoustical measurement while the alternative firmness index (AFI) is based on the impact measurement that evaluates the local surface elasticity. The firmness index (FI) is determined from the resonant frequency of the first elliptical mode and the mass of the fruit[11].

$$FI = \frac{f^2 m^{2/3}}{10^6} \qquad (1)$$

where, FI is the firmness index of fruit samples; f is the first natural or resonant frequency, Hz; m is the fruit weight in grams.

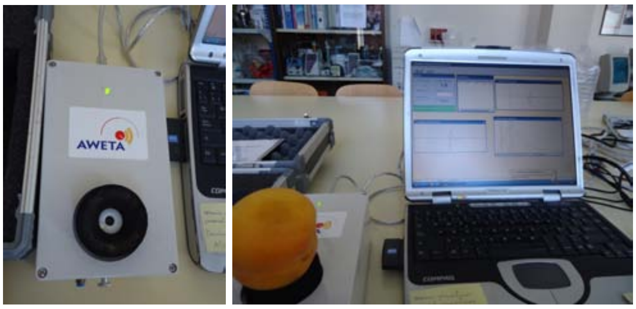


Figure 2 Nondestructive acoustic firmness sensor (AFS)

2.2.2 Low-mass impact sensor by LPF

A lateral low-mass impact sensor developed by Madrid Polytechnic University Physical Properties Laboratory was used in this study (Figure 3).

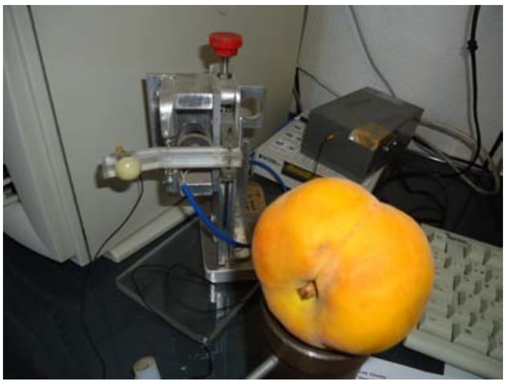


Figure 3 Nondestructive low-mass impact sensor (LPF)

The impact device consists of a spherical low-mass of 10 g, which impacts the sample, with a piezoelectric accelerometer of a sensitivity of 1 mV/m s^{-2} and a range of ±4900 m s^{-2} (ENDEVCO model 256-10 USA), which impacts the fruits to sense its firmness; a spring to release the impacting mass; and an electromagnet to hold the impacting mass. A conditioning circuit supplies power to the accelerometer and also amplifies the acceleration signal. Response of the accelerometer is samples at 40 kHz sampling rate with 12 bit precision DAQ card. A Windows® based software was designed to control all the process which stores data and provides the users with an interface to manage the data and to control the measurement process[9]. Maximum acceleration ($A_{\max}$), measured in m/s^2 was extracted from the deceleration data registered by an accelerometer. This parameter was commonly used as fruit firmness index[5,9,17].

2.2.3 Micro-deformation impact sensor by SIQ-FT

Micro-deformation impact sensor made by Sinclair IQ™ (Sinclair internal quality firmness tester: SIQ-FT) was used for the nondestructive tissue impact response for micro-deformation on the fruit surface (Figure 4). The bench-top version sensor used a pneumatically operated impact head equipped with a piezoelectric sensor. The sensor hits the fruit by an air pressure and captures the impact signal. Its output was processed by proprietary software to return a measure of fruit firmness score as a number indexed from 0 to 100 with 0 being soft and 100 being firm. The firmness, expressed as a SQI (Sinclair Quality Index) value is calculated according to the impact signal as a dynamic measure of fruit tissue spring constant and can be expressed by the following Equation[5,13,15];

$$SQI = C\left[\frac{P_{\max}}{\int p(t)\mathrm{d}t}\right]^2 \qquad (2)$$

where, C is the system constant; $P_{\max}$ is the peak amplitude of the impact response and $p(t)$ is the impact response as a function of time.

Figure 4 Nondestructive micro-deformation impact sensor (SIQ-FT)

The distance between rubber support of sensor and the impact of the fruit was maintained at 25 mm. Vacuum and the operating pressure were adjusted to operate the pneumatic head to within ±1.99 kPa as recommended by the manufacturer. Prior to each use the micro-deformation impact sensor was calibrated using an elastic calibration ball of a known firmness.

For the three nondestructive sensors, six repeated measurements for each peach were taken from three points within the longitudinal axis of the peach for two sides in each test. Data were then averaged for each sensor, and the average of the measurement was supposed to represent peach firmness as a whole.

Sensor data were acquired from each individual sensor. The types of output values are given in Table 1.

Table 1 Data acquisition structure

Sensor type	Sensors	Features	Units
Nondestructive	Acoustic firmness	Firmness index	$Hz^2 \cdot g^{2/3}$
	Low-mass impact	Maximum acceleration	$m \cdot s^{-2}$
	Micro-deformation impact	Quality index	Score
Destructive	Magness-Taylor	Maximum force	N

2.3 Reference measurements

After nondestructive measurements using the three firmness sensors had been completed, the firmness of the tested peaches was measured by standard destructive methods from the same location. The machine used for the reference destructive tests was a Texture analyzer TA-XT2 (STable Micro Systems Ltd., Godalming, U.K.), a universal machine with a texture analyzer microprocessor, it was connected to a PC, and controlled by specific software. The load-cell admits a maximum force of 250 N (resolution 0.0098 N) and an error range of 0.025%. Texture analyzer was used for the mechanical test to determine the firmness group of the test samples and to compare with the nondestructive techniques. Magness-Taylor tests were performed by using an 8 mm diameter probe, at a deformation rate of 18 mm/min on both sides of each fruit at six different points (Figure 1). For destructive measurements, on each labeled place, a piece of skin was removed and Magness-Taylor probe penetrated at least 8 mm into the flesh. Maximum force recorded on the force-deformation curve was selected and used as the measure of fruit firmness being expressed to be Magness-Taylor force (FMT).

The relative firmness loss during the experiment period was calculated as the firmness loss in firmness divided by the initial firmness, multiplied by 100%.

2.4 Statistical analysis

Different sensor fusion techniques such as a high level, an intermediate level and a low level can be used as described by Steinmetz et al.[44]. The high level fusion was performed by using identity declaration provided by each sensor (Figure 5). Since feature-level extraction has already been developed for each individual sensor, the decision-level was applied to the identity declaration level at each individual sensor (Figure 5).

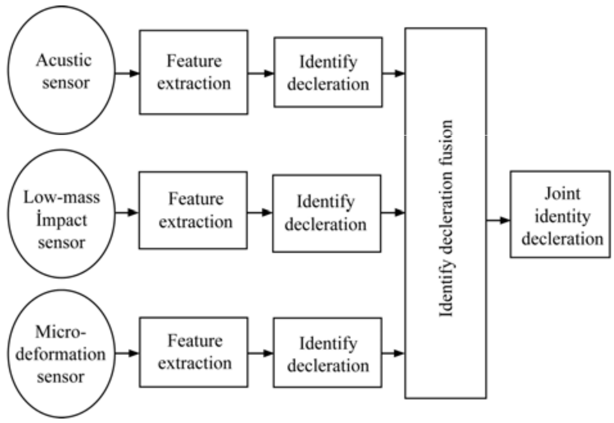


Figure 5 Architecture of high-level fusion

Statistical classification was mainly depended on the Bayes minimum risk classifier. This classifier was applied to each sensor for the firmness evaluation, and for separating the peaches into three categories called soft, intermediate and hard which widely used by the pos-harvest sorters.

The data information of the sensors was processed to output the fused data. Before data fusion is performed, data normalization has to be applied to the raw data provided by the sensors. To improve the classification accuracy of peaches based on their firmness stage as monitored by the sensors, data fusion using Bayesian statistical approach was implemented. Three sensors that output three characteristics and three firmness classes (soft, intermediate and hard) were proposed. In principle, by assuming that data from each individual sensor is independent, the conditional probability density function of data fusion in a three-class problem can be calculated by using the Equation given by Baltazar et al.[47].

$$p(y \mid w_i) = \prod_{j=1}^{m} p_j(x \mid w_i), \quad i = 1, 2, 3, \ldots n \tag{3}$$

where, w_i is the class; n is the number of classes; m is the number of features; y is a pattern vector which corresponds to the fused data; x is a one-dimensional variable and $p(y|w_i)$ is the probability density function for each feature (FI, A_{max} and SQI).

Priori knowledge was used in order to build Bayesian classifier and was set as indicated in Table 2. These values were chosen based on the knowledge of the properties of each variety, and the ratios were arbitrarily chosen with the help of an expert in order to take into account this knowledge. Each sample tested at different firmness stages was processed successively through the three individual sensors for nondestructive measurements described in Section 2.2. The variety of the peaches appears to be an important factor in order to refine at the decision level because it influences the probability of occurrence of the firmness classes for each variety.

Table 2 A priori probabilities determined for each variety

Quality/Variety	Soft	Intermediate	Hard
Royal Glory	0.90	0.07	0.03
Caterina	0.91	0.08	0.01
Tirrenia	0.58	0.37	0.05
Suidring	0.54	0.06	0.4

Destructive measurements described in Section 2.3 were used as reference firmness of peaches, and the peaches were classified into three classes "soft", "intermediate" and "hard". A three-group firmness classification was created by using a 18-35 N Magness-Taylor force threshold. Therefore, peaches between 18-35 N were considered "intermediate". The peaches below 18 N and above 35 N were defined as "soft" and "hard", respectively. These firmness thresholds were selected because of critical change of peaches during postharvest ripening and the susceptibility to bruising damage[15].

Furthermore, other peach samples that did not belong to these classes were classified into two fuzzy classes: "intermediate or soft" for the samples that belongs sometimes to the "soft" or sometimes "intermediate" firmness class, and "intermediate or hard" for the samples that belongs sometimes to the "hard" or sometimes "intermediate" class. By using this process five classes were created.

The correlation coefficient indicates the strength of a linear relationship between two variables, and is the most interesting parameter before performing the fusion process. The test for linearity of regression between nondestructive sensors and the destructive reference measurement (Magness-Taylor force) was made, and a confidence interval (90%) was computed for the correlation coefficient. The correlation coefficients provided a check to be made on which sensor were redundant or complementary between two sensors, and produced some knowledge about the validity of the destructive reference measurement.

The chi-square (χ^2) test was used to determine whether there was a significant difference between the classification made by a nondestructive sensor and the classification made by the destructive sensor. For each nondestructive sensor, the largest χ^2 value indicated the nondestructive sensor that was most closely related to the destructive sensor.

The coefficient of contingency (C) can be computed using Equation (4):

$$C = \sqrt{\frac{X^2}{n(q-1)}} \tag{4}$$

where, n is the sample number and q is the class number.

The coefficient C provided a measure of association between the classification made by the sensors. This coefficient is interesting because it provides the performance of the fusion on a normalized scale. The value of C was computed based on the χ^2 values.

3 Results and discussion

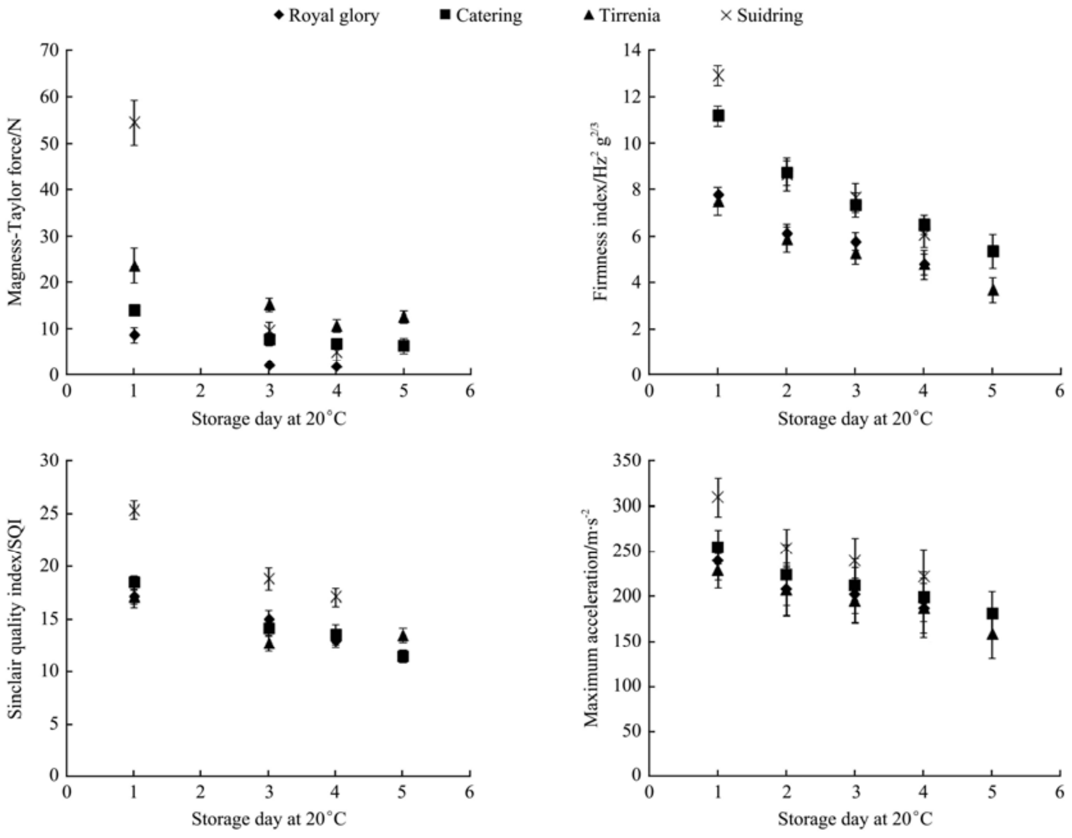
The correlation values and 90% confidence intervals between the sensors were given in Table 3. Table 3 shows the sensor similarities based on raw data. For a linear regression model between nondestructive and destructive measurements, the confidence intervals of the correlation coefficients from sensor "acoustic firmness" and low-mass impact" do coincide. It means that the percentage of variation in the firmness measurement does not change significantly at a 90% confidence level from acoustic firmness sensor to low-mass impact sensor. The correlation coefficient between the nondestructive sensors and destructive was found different for the micro-deformation sensor.

Figure 6 shows the mean peach firmness loss for four peach varieties, as perceived by the destructive and three nondestructive sensors. It can be observed that all four devices are capable to sense the firmness loss of the peaches during the experiment. The relative firmness loss during the experiment period for "*Royal Glory*" in the case of Magness-Taylor force was 82.71%, for the Aweta 38.27%, for the SIQ-FT 24.09% and for the LPF 21.73%. These values for "*Caterina*" variety were found to be 55.60%, 52.01%, 38.22% and 28.58%, respectively. The mean firmness losses for "*Tirrenia*" and "*Suidring*" varieties in the case of Magness-Taylor force were 47.13% and 91.20%, for the Aweta 51.07% and 52.67%, for the SIQ-FT 21.04% and 32.62% and for the LPF 30.54% and 28.24%. It means that peaches loose more firmness in case of Magness-Taylor force compared to Aweta, SIQ-FT anf LPF, respectively. Furthermore, for the Magness-Taylor force, the firmness loss was more pronounced in the first day of the experiment whereas the decline was observed almost in the whole period for Aweta, SIQ-FT and LPF as can be found in Figure 6.

Table 3 Correlation coefficients and 90% confidence intervals between the sensors

	Acoustic firmness	Low-mass impact	Micro-deformation	Magness-Taylor
Acoustic firmness	1	0.861**	0.779**	0.663**
Low-mass impact		1	0.913**	0.684**
Micro-deformation			1	0.766**
Magness-Taylor				1

Note: ** Correlation is significant at the 0.01 level.



Note: The vertical lines indicate the standard deviation.

Figure 6 Mean peach firmness loss during storage day at 20°C for destructive and three nondestructive sensors

The results for unsupervised firmness classification based on the destructive firmness sensor were given in Table 4. Furthermore, the decision boundaries used by experts[15] for classification of peach firmness were presented in Table 5. The classification given in Table 5 were found to be similar to the firmness classes provided by unsupervised firmness classification since the mean values of the two fuzzy classes "soft or intermediate" and "intermediate or hard" were more or less similar to the limits used by the expert. Unsupervised classification allows classes to be defined without firm limits. These fuzzy classes allow inclusion of samples for which it is not easy to determine the correct classification between "intermediate" and "hard" firmness classes.

Tables 6-8 show the number of peaches resulting from the classification of three nondestructive sensors with a Bayesian classifier. The classification performance was evaluated by computing the number of errors. As a general rule, an error occurs when the constituted firmness class provided by the nondestructive sensor is different from the firmness class constituted by the destructive reference measurement. The percentage error was defined as the total number of errors divided by the total number of samples. It can be seen from Tables 6-8 that the total error rate of the classification of micro-deformation impact sensor is 19%, lower than the acoustic firmness and low-mass impact sensor. Values for acoustic firmness and low-mass impact sensor were found to be 25% and 24%, respectively. The source of classification error for the three nondestructive sensors can be due to the small size of the middle and hard samples assigned randomly. Furthermore, it could also come from the destructive reference measurements even though all the nondestructive sensors agree.

Table 4 Results for unsupervised firmness classification of destructive reference measurement for four peach varieties

Quality	Soft	Soft or Intermediate	Intermediate	Intermediate or Hard	Hard
Number of fruits	91	26	2	7	10
Mean	**6.07**	16.14	**26.29**	29.87	**54.69**
Standard deviation	4.81	8.90	11.08	12.74	7.43
Min	0.91	1.66	18.5	18.39	41.13
Max	**18.08**	29.36	**34.13**	53.44	**64.34**

Table 5 Peach firmness classification used by experts[15]

Quality	Soft	Intermediate	Hard
Magness-Taylor	<18	$18 \le x < 35$	$x \ge 35$

Table 6 Classification for acoustic firmness sensor

	Destructive reference measurement				
	Soft	Soft or Intermediate	Intermediate	Intermediate or Hard	Hard
Nondestructive sensors					
Soft	100	0	2	1	0
Intermediate	20	0	0	1	0
Hard	2	0	9	0	1

Note: Total error: 25%.

Table 7 Classification for low-mass impact sensor

	Destructive reference measurement				
	Soft	Soft or Intermediate	Intermediate	Intermediate or Hard	Hard
Nondestructive sensors					
Soft	103	0	0	0	0
Intermediate	0	21	0	0	0
Hard	0	0	0	12	0

Note: Total error: 24%.

Table 8 Classification for micro-deformation impact sensor

	Destructive reference measurement				
	Soft	Soft or Intermediate	Intermediate	Intermediate or Hard	Hard
Nondestructive sensors					
Soft	101	0	0	2	0
Intermediate	19	0	0	2	0
Hard	0	3	0	0	9

Note: Total error: 19%.

Results of fusion classification by using three nondestructive sensors were given in Table 9. These results were obtained through a Bayesian classifier associated with each individual sensor, and the fusion classification method. Results of Table 9 should be compared with the classification given by each individual sensor as shown in Tables 6-8. The fusion processes decreased the classification error rate from 19% to 13%. Even though there was a decrease in error rate value determined by using all the nondestructive sensors some peaches were assigned to different firmness classes. For instance, the classification of the peaches into class "soft", could not be improved if they actually belonged to class "intermediate" or "hard". These classification errors can be due to the fact that only one feature was used (A_{max}) from the low-mass impact sensor because other features that can be used for low-mass impact sensor such as impact duration at maximum acceleration, maximum acceleration/impact duration at maximum acceleration, maximum deformation, contact time were not taken into consideration in present study. Furthermore, the numbers of peaches used in our study for soft, intermediate and hard firmness groups of all the peach varieties were 103, 21 and 12, respectively. It should be taken into consideration that the big difference in the numbers of samples among the three firmness groups and small numbers of intermediate and hard peaches will impair the total error rate of the firmness classification even though unsupervised classification was made to build the classes based on destructive reference measurement. Lastly, six measurements were made for each peach, and these data were averaged. This can be a source of error for the classification because averaging leads to a loss of information.

Table 9 Classification for the fusion process by using three nondestructive sensors

	Destructive reference measurement				
	Soft	Soft or Intermediate	Intermediate	Intermediate or Hard	Hard
Nondestructive sensors					
Soft	100	3	0	0	0
Intermediate	16	0	2	3	2
Hard	1	0	0	1	10

Total Error: 13%.

Table 10 describes the results when one of the sensors was removed from the fusion process. As seen in Table 10, fusion of the acoustic sensor with low-mass impact sensor or micro-deformation sensor does not change the classification error rate sufficiently. However, fusion of the low-mass impact and micro-deformation impact sensors without acoustic firmness sensor provided a classification error rate which was higher than the one provided by the fusion system with the three nondestructive sensors. In the fusion process, the three sensors should be fused in order to obtain the best results with an error rate value of 13%.

Table 10 Classification results by removing one of the nondestructive sensors

Sensor combination	Error rate/%
Acoustic firmness and low-mass impact	23
Acoustic firmness and micro-deformation impact	21
Low-mass impact and micro-deformation impact	17

Table 11 shows the different computed values of χ^2 and C for each nondestructive sensor. χ^2 values were computed based on the results of the classification of each sensor, and the results of the fusion sensor classification. χ^2 values given in Table 11 showed that micro-deformation impact sensor gave the best classification with a χ^2 value of 272.00. Contingency coefficient (C) values were computed based on the χ^2 values from Table 11. C value computed for the micro-deformation sensor was found higher than the C values of other two sensors. Furthermore, the correlation coefficient value for the fusion process of three nondestructive sensors with a correlation coefficient of 0.84 was found larger than any other coefficient given in Table 11. This situation shows us that the fusion process was efficient in improving the classification. Furthermore, it can be seen that the order of the C coefficients confirms the classification of nondestructive sensors that was found with the correlation coefficient.

Table 11 χ^2 and coefficient of contingency (C) values for the different sensors

Destructive measurement	Nondestructive sensors	χ^2 values	Prob.	C	Prob.
Magness-Taylor force	Acoustic firmness	93.000**	0	0.637**	0
	Low-mass impact	139.523**	0	0.712**	0
	Micro-deformation impact	272.000**	0	0.816**	0

4 Conclusions

In the present study, the possibility of fusing the nondestructive firmness sensors (acoustic firmness, low-mass impact and micro-deformation impact) was evaluated with data fusion approach for firmness classification of four peach varieties. This fusion process integrated the features extracted from each individual sensor, and associated them with a Bayesian classifier which performed a joint identity declaration of peaches among three firmness classes namely, soft, intermediate and hard. Correlation coefficient, χ^2 test and coefficient of contingency were described in order to determine whether the fusion method enhance the firmness classification or not. All the coefficients showed that the fusion process was more efficient than any individual sensor. In the case of fusion process, results demonstrated that each sensor had varying abilities of sensing firmness. High level fusion technique performed by using identity declaration led to greatly improved and more consistent classification of firmness. The fusion of three nondestructive sensors decreased error rate to 13% while it varied from 25% to 19% for each individual sensor. Significantly better firmness classification was obtained with an error rate of 17% when a low-mass impact sensor was fused with a micro-deformation impact sensor. Fusion process used in the present study can also be applied to measure various external or internal properties of fruits. It should be noted that harvest season, variety variation and growth conditions can influence the Bayesian classification since statistical parameters that define the prior probabilities might change. On principle, data fusion methodology described in our study can be used in order to extrapolate to other postharvest products which the quality control of products is also necessary. But, it is important to consider the big difference in the numbers of samples among the firmness groups which would impair the overall accuracy rate and reliability of firmness classification. Further research based on the sensor fusion technique for firmness classification of other fruit species is needed in order to develop a more accurate system by using a wider number of parameters for each individual sensor.

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