A Spectroscopy-Based Approach for Automated Nondestructive Maturity Grading of Peach Fruits

Stefania Matteoli, *Member, IEEE*, Marco Diani, *Member, IEEE*, Rossano Massai, Giovanni Corsini, *Member, IEEE*, and Damiano Remorini

***Abstract*— This paper presents an automated approach for peach fruit maturity grading that, by exploiting fiber-optic spectroscopy-based sensors and multivariate processing techniques, minimizes the operator intervention while reducing discharge and waste. The use of a spectroscopic sensor complies with the so-called nondestructive measurement method, which enables fast repeated measurements to be performed at the single fruit level while avoiding fruit damage and loss. Maturity grading is accomplished by retrieving estimates of the fruit flesh firmness by means of multivariate retrieval techniques applied to the reflectance spectra acquired with the spectrometer and by processing the retrieved values within the framework of a maturity fuzzy classifier. A decision support system is developed to provide the user with maturity category decision and associated reliability. Experimental results show that the approach is effective for automated maturity grading of peach fruits affected by a high degree of variability. This paper lays the foundations for the realization of easy-to-use sustainable automated maturity grading systems.**

***Index Terms*— Fiber-optic spectroscopy, reflectance, non-destructive approach, maturity grading, ripeness assessment.**

I. INTRODUCTION

PEACH fruits play an important role in human diet from both economic and nutritional points of view. They represent a significant component of the diet during the spring and the summer, with the largest mass consumed per person among stone fruits [27]. Peaches are low-calorie no-saturated-fat fruits that are a rich source of antioxidants, vitamins, and minerals. The flavonoids polyphenolic compounds they contain have been shown to help warding off obesity-related diseases such as diabetes, metabolic syndrome, and cardiovascular disease [24]. More recently, the polyphenols of selected peach genotypes have been shown to reduce proliferation of breast cancer cells [21], [36] and consumption of 2 or 3 peach fruits per day [21] is likely to become a chemo-preventive dietary regime pursued by more and more health-conscious consumers.

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Key to the commercial expansion of peach fruit production is the achievement and preservation of the highest possible standards of fruit quality [27], in terms of both commercial and consumer-oriented perspectives [31]. Commercial quality requires a longer *shelf-life* and maximum resistance to mechanical damage, whereas consumer-oriented quality is associated with consumer wants and needs such as sensorial, nutritional, and nutraceutical attributes [27], [31].

Fruit maturity has a major impact on fruit quality, which is determined by all biochemical, physiological, and structural changes occurring during fruit ripening (e.g. changes in color, sugar content, and flesh firmness as well as nutraceutical compounds increase, organic acid decrease, volatile and aromatic substances development [31]).

Climacteric fruits such as peach fruits can be harvested when mature and ripened off the plant [9], [23]. Fruit maturity stage at harvest determines the ultimate fruit quality and shelf-life and is essential to subsequent fruit sorting towards different distribution channels. However, it is difficult to identify a harvesting time that represents the best trade-off between consumer-oriented and commercial qualities [27]. A fruit that is harvested when is fully ripe has better organoleptic properties but has a shorter shelf-life, being ready-to-eat and, thus, more susceptible to softening and decay. Conversely, fruits early-harvested when mature or under-mature have an increased shelf-life and may undergo longer post-harvest handling chains.

Therefore, measures of maturity stage need to be performed before harvest, in the orchard, so as to find the optimal harvest date for the intended use, and just after harvest, at the packing facility or in the warehouse, to assess fruit shelf-life and determine the most suitable handling chain and marketing channel.

Goal of this work is to develop a novel automated approach for grading peach fruits according to maturity stage. The approach is intended to be embedded in automated systems that should be easy-to-use by non-experts, minimize the operator intervention, and avoid discharge and waste. With respect to other works where the so-called "optimal harvesting window" is sought that indicates when fruits can be picked and endure storage while maintaining good quality [5], [22], here the aim is accurately grading peach fruits within several different specific maturity categories, covering the whole ripening range from immature to over-ripe fruits. In fact knowledge of the specific maturity category is important to select the best storage condition and distribution channel.

For instance fully ripe fruits are promptly distributed to local markets, mature and under-mature fruits are generally delivered to supermarkets and wholesales, and over-ripe fruits may be rapidly sold in local farmer's markets or – when unmarketable – kept for alternative markets, such as juice, functional foods, and pharmaceutical.

Several indicators may serve the maturity grading purpose, such as fruit flesh firmness, soluble solid contents, and titratable acidity, which are generally measured with laboratory analyses [1], [27], [38]. Specifically, maturity stage of some of the most commercially popular peach fruits, such as the yellow-fleshed 'Flavorcrest' peach, has been shown to correlate well with flesh firmness (FF) [26], [27], because fruit softening is ruled by ethylene production occurring during ripening [9]. Measures of FF can be carried out by piercing the flesh of the fruit with a penetrometer [1]. Nonetheless, this is a time-consuming method that entails sample fruit destruction and, thus, enables FF measures at the batch level rather than at the individual fruit level. An effective alternative is resorting to a non-destructive measurement approach [6], [20], [26], which makes use of remote/proximal sensors, e.g. high-resolution fiber-optic spectrometers, to retrieve fruit properties such as FF by suitable processing of the fruit reflectance spectra, thus avoiding fruit damage and waste and, in turn, allowing faster, repeated measures on each fruit of the batch. This non-destructive approach has recently been pursued in several other fields of food safety and control besides the fruit sector [13]–[19], as the wide availability of bright LED illuminators and portable and ultra-compact spectrometers, along with the desired properties inherent to optical fibers, enables implementation of low-cost compact instrumentation with great potential in this field [14], [15].

The proposed maturity grading approach is based on four main steps. First, reflectance spectra of all peach fruits of the batch are acquired using a suitable spectrometer operating in the VISible (VIS) Near-InfraRed (NIR) range. Then, FF estimates are retrieved for each fruit by exploiting multivariate techniques and the availability of FF destructive measurements previously performed on a subset of the fruits (i.e., the "training" fruit samples). The retrieved FF estimates are then processed within a maturity FF-based classification framework based on fuzzy logic, which avoids sticking with strict maturity stage categories and rigorous decision rules while enabling the design of a decision support system. Finally, the user is provided with maturity category decision, ranking of maturity categories and associated reliability levels.

Experimental results featuring 840 'Flavorcrest' peach fruits originating from four different batches and affected by a very high degree of variability are presented that represent a proof-of-concept that the proposed approach is effective for computer-assisted automated non-destructive fruit maturity grading.

The paper is organized as follows. Section II describes in detail the proposed approach. Materials and methods employed are described in Section III. Experimental results are presented and discussed in Section IV and Section V summarizes the main contributions of the paper.

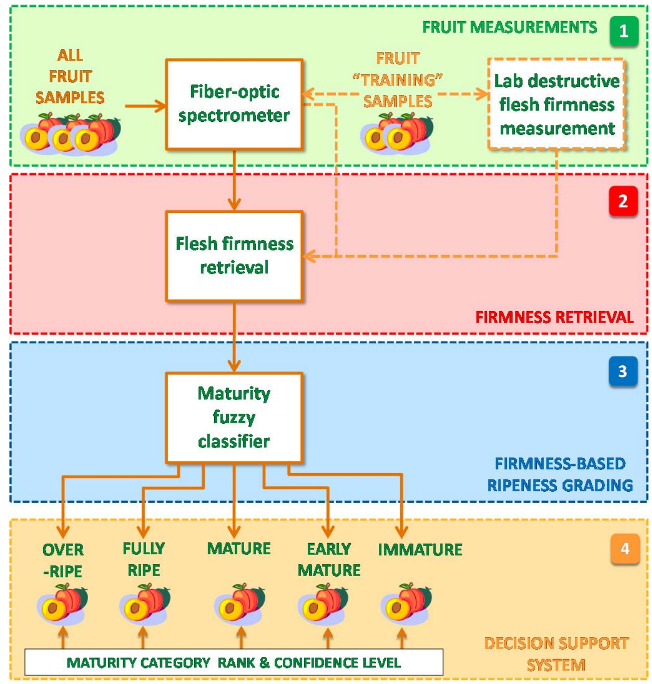

Fig. 1. Conceptual block diagram of the proposed peach fruit maturity grading approach.

II. Peach Fruit Maturity Grading Approach

This section describes in detail the proposed approach for automated maturity grading of peach fruits. A conceptual block diagram of the overall approach is depicted in Fig. 1.

A. Fruit Measurements

The first step of the approach consists in performing measurements on peach fruits. All fruits to be inspected are spectrally characterized by collecting the spectral diffuse reflectance of fruit skin with a VIS-NIR spectrometer. In the perspective of realization of automated grading systems, such measurements may be performed while the fruits move along the grading line by means of sensors installed on suitable platforms or conducted directly on the tree by using a portable compact spectrometer.

A given number of fruits (generally a low percentage of the whole batch) should have been previously retained as fruit "training" samples that undergo not only spectral characterization, but also preliminary destructive measurements of FF. These training samples are used in the second step to "learn" the relationship between FF and spectral reflectance so that FF estimates can be retrieved for the remaining fruits just by suitable processing of the acquired spectra.

B. Flesh Firmness Retrieval

Goal of the second step is to retrieve the FF of each given peach fruit. It is important to note that we do not strive towards obtaining the highest possible retrieval accuracy (with, perhaps, FF retrieval precision of the order of a few grams). Rather, we just need the retrieval accuracy to be high enough to enable a proper operation of the maturity classifier in the third step.

Several methodologies may be used to retrieve FF values from the acquired reflectance spectra of peach fruits. In some works [26], [33]–[35], reflectance indexes (e.g. band ratios) are extracted from fruit spectra and correlated to destructive measures of FF via linear regression. The regression coefficients are then used to infer the FF of the remaining fruits. This way, just a few spectral bands are examined and the rich information content enclosed in the spectra is not fully exploited. Hence, another approach is to employ multivariate regression techniques such as principal component regression (PCR) or partial least square regression (PLS), which employ the entire spectra shape while by-passing the problem of multi-collinearity of the predictor matrix [2], [20].

According to such an approach, the $[1 \times s]$ vector $\widehat{\boldsymbol{FF}}$ of retrieved FF estimates, being s the number of fruit samples, is obtained as follows:

$$\widehat{\boldsymbol{FF}} = \boldsymbol{\beta}^T \cdot \boldsymbol{R} \tag{1}$$

where $\boldsymbol{\beta}$ is the $[b \times 1]$ vector of PCR or PLS regression coefficients, with b indicating the number of measured spectral bands, and $\boldsymbol{R}$ is the $[b \times s]$ (predictor) matrix of reflectance spectra. The regression coefficients are found by exploiting the training fruit samples for which the true FF values are known by destructive measurements.

In this work, we choose to adopt the PLS method [2], [16], [20], which has become an established approach for predicting response variables (i.e., the FF in this case) from a highly collinear predictor matrix, especially in fruit quality monitoring. Specifically, the PLS derives the regression coefficients by seeking for the set of linear combinations of the predictors that are orthogonal and maximize their covariance with the response variables [2].

C. Maturity Fuzzy Classifier

Goal of the third step is to classify the peach fruits in suitable maturity categories on the basis of the retrieved FF values.

1) Definition of Maturity Categories by Fuzzy Logic: In many situations people are only able to characterize numeric information imprecisely. This is the case of an agronomist or a fruit grower that has to define maturity categories for peach fruits based on FF values. For example, they may say that a peach fruit of a given cultivar is to be considered fully ripe when its FF is low, but not too low, such as lying approximately within a given range of FF values.

When a mathematical model is difficult to derive, information is more easily represented in terms of *linguistic variables* (e.g., "high/low" FF), or numeric information cannot be characterized precisely, fuzzy logic comes in help by enabling approximate human reasoning to be applied to knowledge-based systems [39]. The fuzzy logic approach is particularly suitable to cope with fruit maturity category definition and classification because avoids sticking with rigorous maturity categories and strict decision rules while combining human heuristics into computer-assisted decision-making [7].

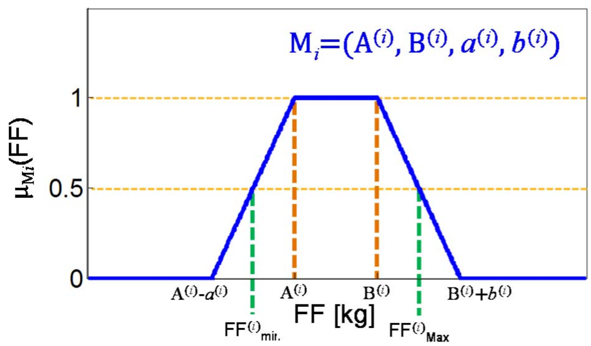

Fig. 2. Generic trapezoidal fuzzy membership function used to model the i-th maturity category M_i represented by a fruit FF value approximately lying within the $\left[FF_{min}^{(i)}, FF_{Max}^{(i)}\right]$. In the figure, $a^{(i)} = b^{(i)}$.

Here, FF-based maturity categories are defined by resorting to fuzzy sets, where the membership degree of a given fruit to the set is defined by a real number and the so-called universe is made of all possible values of FF. Each maturity category is thus "fuzzified", i.e., associated with a fuzzy membership function that allows for a gradual transition from membership to non-membership, thus making the class boundaries less distinct and more, indeed, fuzzy.

In this work, for the generic i-th maturity category M_i represented by a fruit FF value approximately lying within the $\left[FF_{min}^{(i)}, FF_{Max}^{(i)}\right]$ interval, the corresponding membership function $\mu_{M_i}(FF)\colon FF \to [0, 1]$ is defined as follows:

$$\mu_{M_i}(FF) = \begin{cases} 1 - \dfrac{A^{(i)} - FF}{a^{(i)}} & A^{(i)} - a^{(i)} \leq FF \leq A^{(i)} \\ 1 & a^{(i)} \leq FF \leq B \\ 1 - \dfrac{FF - B^{(i)}}{b^{(i)}} & A^{(i)} \leq FF \leq B^{(i)} + b^{(i)} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where the function core $\left(A^{(i)}, B^{(i)}\right)$ is determined by $A^{(i)} = FF_{min}^{(i)} + a^{(i)}/2$ and $B^{(i)} = FF_{Max}^{(i)} - b^{(i)}/2$, the scalars $a^{(i)}$ and $b^{(i)}$ enables definition of the function support $\left(A^{(i)} - a^{(i)}, B^{(i)} + b^{(i)}\right)$, and the index i goes from 1 to the total number of maturity categories N_C. A concise notation for equation (2) is $M_i\left(A^{(i)}, B^{(i)}, a^{(i)}, b^{(i)}\right)$ and a graphical representation of such membership function is provided in Fig. 2. The parameters $FF_{min}^{(i)}$ and $FF_{Max}^{(i)}$ of each membership function have to be set by an agronomist or a peach grower on the basis of previous experience.

Within the maturity grading framework, it makes sense to allow intersection only between membership functions of adjacent categories. The more they intersect, the less definite is the transition between the two categories. Also, in correspondence to the core of a given membership function, the other functions need to be zero.

2) Classification With Respect to Maturity Categories: In general, classification of peach fruits with respect to N_C maturity categories can be cast in terms of multiple-hypotheses testing [8]:

$$\left\{H_i : \widehat{FF} \in M_i\right\}_{i=1}^{N_C} \tag{3}$$

where fulfillment of the generic i-th hypothesis means that the fruit with retrieved FF equal to $\widehat{FF}$ belongs to the maturity category M_i.

Once the maturity categories are defined and "fuzzified", the multiple-hypotheses decision problem in equation (3) may be approached by deriving a suitable decision rule on the basis of the maturity membership functions. Specifically, the decision rule aims at assigning each fruit to the maturity category that exhibits, in correspondence to the retrieved $\widehat{FF}$ value, the highest membership function – with a confidence level given by the membership function value itself:

$$H_{j_1}\left(\widehat{FF} \in M_{j_1}\right) : \begin{cases} j_1 = \underset{i=1,\cdots,N_C}{\arg\max} \left\{\mu_{M_i}\left(\widehat{FF}\right)\right\} \\ C_{j_1} = \mu_{M_{j_1}}\left(\widehat{FF}\right) \end{cases} \tag{4}$$

The decision rule in equation (4) means that the given fruit is assigned to the M_{j_1} maturity category, which ranked 1st among the other categories, with confidence level C_{j_1}.

Given the difficulty in providing distinct decision boundaries for the maturity categories and benefiting from the availability of confidence levels, a precautionary approach may be adopted in which a ranking of candidate categories are provided as output, sorted according to a descending order of the corresponding confidence levels, as follows:

$$\left\{H_{j_k}\left(\widehat{FF} \in M_{j_k}\right)\right\}_{k=1}^{K} : \left\{\begin{array}{l} j_k = \underset{\substack{i=1,\cdots,N_C \\ j \neq j_{m<k}}}{\arg\max} \left\{\mu_{M_i}\left(\widehat{FF}\right)\right\} \\ C_{j_k} < C_{j_{m<k}} \end{array}\right\}_{k=1}^{K} \tag{5}$$

Since here we allow intersection only between membership functions of adjacent categories, $K = 2$ in equation (5) because $C_{j_{k>2}} = 0$.

D. Decision Support System

At the end of the previous step, the user is provided with maturity category "crisp" (non-fuzzy) decision (i.e., M_{j_1}), ranking of maturity categories (i.e., $\left\{M_{j_k}\right\}_{k=1}^{2}$) and associated confidence levels (i.e., $\left\{C_{j_k}\right\}_{k=1}^{2}$, $C_{j_1} > C_{j_2}$). In order to assist the user and support the decision-making process, reliability levels can be defined on the basis of ranges of values of the confidence levels, such as (i) '*Maximum reliability*' for $C_{j_k} = 1$, (ii) '*High reliability*' for $0.75 \leq C_{j_k} < 1$, (iii) '*Moderate reliability*' for $0.65 \leq C_{j_k} < 0.75$, (iv) '*Low reliability*' for $0.5 \leq C_{j_k} < 0.65$. Therefore, besides the crisp category decision M_{j_1}, the user can rely upon the reliability levels in order to accept such decision or, in case for instance of moderate or low reliability, choose to consider the maturity category M_{j_2} that ranked 2nd based on additional factors (e.g. peach fruit color) or retain the given peach fruit for further inspections. A synoptic chart should be provided to the user summarizing all this information in support to a simple and quick decision-making process.

III. Materials and Methods

A. Peach Fruit Data Set

840 'Flavorcrest' yellow-fleshed peach fruits coming from 4 different batches and grown on 50 different peach trees within the orchard of the DAFE experimental farm of the University of Pisa (Italy) were involved in this study.

The fruits were affected by a very high within-orchard and within-plant variability. In fact, the trees were grafted onto several different rootstocks and subject to different summer pruning treatments, and peach fruits of a same tree were exposed to different level of solar radiation. All these aspects ultimately affect the fruit maturation process.

The 840 peach fruits belonged to four different batches depending on whether the fruits were harvested before, around, or after the assumed "optimal harvest date" (i.e. the date at which the fruits would be ripe or nearly ripe according to the fruit grower experience): 1) "*Very early harvest*" batch included fruits harvested approximately two weeks before the "optimal harvest date"; 2) "*Early harvest*" batch included fruits harvested approximately one week before the "optimal harvest date"; 3) "*Middle harvest*" batch included fruits harvested approximately around the "optimal harvest date"; 4) "*Late harvest*" batch included fruits harvested approximately one week after the "optimal harvest date". This peach fruit data set is highly variable in terms of maturation level of each given fruit, ranging from immature to over-ripe fruits. Thus, it is particularly suitable to test the proposed maturity grading system.

Within a 3-fold cross-validation framework, the 840 peach fruits were partitioned into three equal sized subsets. Two subsets were merged and retained as set of "training" fruit samples, whereas the remaining one was employed as "test" set of fruit samples to be used for performance evaluation. The procedure was repeated three times, with each of the three subsets used once as the "test" set. Performance indexes were averaged over the three cross-validation trials. Although a much lower fraction of fruits should be used for training purposes in operational applications, the 1:2 proportion between test and training samples is not only consistent with many other works in the literature [29], [30], [37] but also sufficient to provide proof-of-concept of the effectiveness of the proposed approach. Investigation into varying the sample size is beyond the scope of this paper and will be addressed in future works.

B. Destructive and Non-Destructive Measurements

Destructive and non-destructive measurements were carried out at harvest.

1) Destructive Measurements: FF was measured with a digital penetrometer having a 8-mm probe (model 53205, TR, Forlì, Italy) on a flat surface obtained by removing the skin from two sides of the fruit. The measure was performed on two opposite faces in the equatorial zone. FF was expressed in kg. Histograms of FF measurements for the four peach fruit batches are shown in Fig. 3(a-d). As is evident, the later the fruits are harvested, the softer the flesh is (i.e., FF is lower).

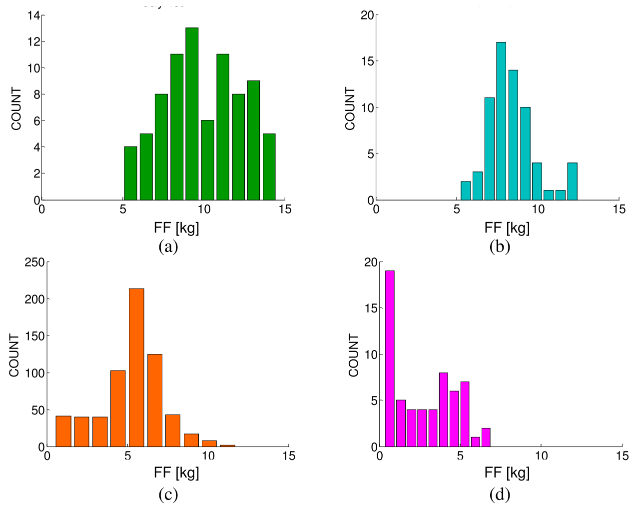

Fig. 3. Histograms of FF (in Kilograms), destructively measured with a penetrometer. (a) "Very early harvest" peach fruit batch. (b) "Early harvest" peach fruit batch. (c) "Middle harvest" peach fruit batch. (d) "Late harvest" peach fruit batch.

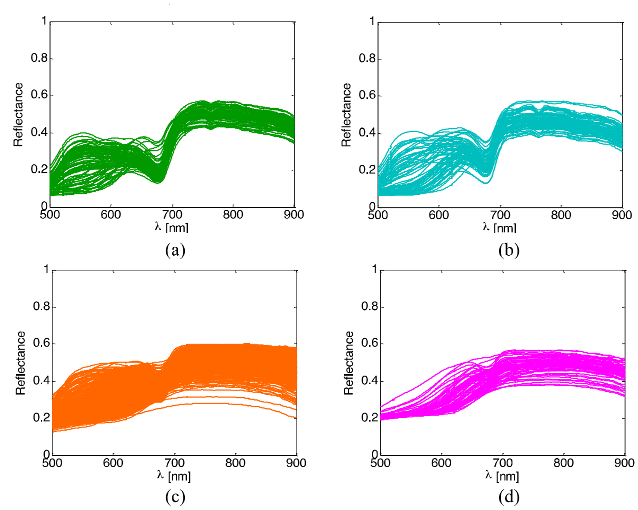

Fig. 4. Plots of reflectance spectra, remotely measured with a fiber-optic spectrometer. (a) "Very early harvest" peach fruit batch. (b) "Early harvest" peach fruit batch. (c) "Middle harvest" peach fruit batch. (d) "Late harvest" peach fruit batch.

Nonetheless, a very high FF variability can be observed within each batch.

2) Non-Destructive Measurements: Diffuse reflectance of fruit skin was collected in the VIS-NIR range with a HR2000 fiber-optic Spectrometer coupled with an integrating sphere (Ocean Optics, Dunedin, FL, USA). The spectrometer was equipped with a DH2000 tungsten lamp and provided measures with a spectral sampling of the order of 0.5 nm. Noisy channels were removed and 900 spectral channels within the [500, 900] nm range were retained for processing. Plots of fruit reflectance spectra for the four peach fruit batches are shown in Fig. 4(a-d). The differences in maturation level across the four batches appear evident by looking at the spectra. In fact, physical and biochemical phenomena occurring during ripening manifest themselves throughout the spectra. For instance, changes in color affect the spectra in the VIS wavelengths whereas chlorophyll degradation occurring during ripening reveals itself as an increase in the reflectance within 650 and 720 nm [33]. Fig. 4 also confirms the high within-batch variability already observed in Fig. 3.

C. Experimental Design

The spectra were pre-processed with conventional techniques such as spectral binning, centering, and smoothing. It should be noted that, contrary to what is done in most works [20], [29], [30] where many combinations of pre-processing algorithms are tested and the one providing the best performance on the training sample data is retained, here we choose to make things easier and more straightforward by selecting one fixed simple pre-processing chain, since the slight retrieval performance differences that may derive from application of diverse pre-processing chains are absorbed into the fuzziness inherent to the classification approach.

PLS regression was applied to the pre-processed spectra and the number of PLS components was automatically chosen by resorting to 5-fold cross-validation, i.e. by minimizing the mean square prediction error on the training samples estimated by cross-validation.

TABLE I

FF-BASED MATURITY CATEGORIES FOR 'FLAVORCREST' PEACH FRUITS AS RECOMMENDED BY THE AGRONOMIST

#	FF [kg]	MATURITY CATEGORY
1	< 3	OVER-RIPE
2	3 ≤ FF < 5	FULLY RIPE
3	5 ≤ FF < 7	MATURE
4	7 ≤ FF < 9	EARLY MATURE
5	FF ≥ 9	IMMATURE

Application of the maturity fuzzy classifier required maturity categories to be defined. Similarly to what is done in the literature [35], these were defined based on range of FF values. The resulting FF-based maturity categories for the 'Flavorcrest' peach fruits as recommended by the agronomists [28] are reported in TABLE I. The table provides the $\left[FF_{min}^{(i)}, FF_{Max}^{(i)}\right]$ interval for each of the five identified maturity categories, i.e. M_1) "over-ripe", M_2) "fully ripe", M_3) "mature", M_4) "early mature", and M_5) "immature". The fuzzy membership functions associated with such maturity categories are plotted in Fig. 5. As is evident, the domain corresponding to values of the membership function of a given category higher than 0.5 matches the FF range provided by the agronomist for that category.

D. Performance Indexes

Performance evaluation is carried out exploiting test fruit samples.

Intermediate FF retrieval results may be evaluated by reporting the Root Mean Square Error of Prediction (RMSEP), which is a standard performance index for assessing regression

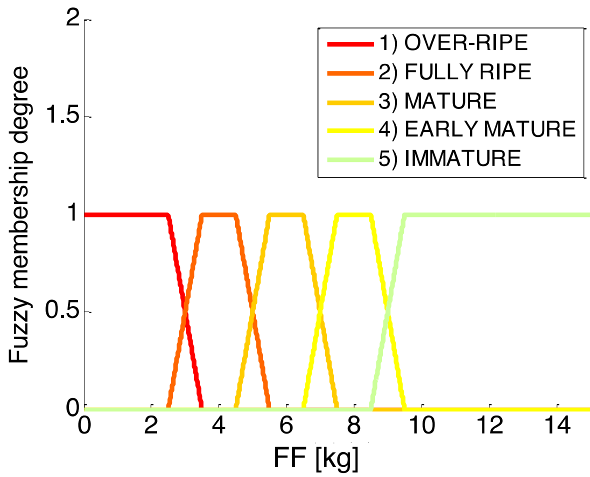

Fig. 5. Plots of fuzzy membership functions for maturity categories of "Flavorcrest" peach fruits.

performance indicating that the results of future predictions can be expressed – with a 95% confidence interval – as the predicted value ±1.96·RMSEP. A more reliable performance measure may be evaluated as The Root Median Square Error of Prediction (RMedSEP), because the median is a much robust estimator of the central tendency of a distribution with respect to the mean, especially when the data are susceptible to outliers. The value of the coefficient of determination R^2 – computed on the training fruit samples – may also be considered, which measures how well FF correlates with the reflectance spectra by means of the PLS regression coefficients.

The ultimate maturity grading performance can be assessed by evaluating the classification accuracy. The per-category accuracy [32], expressed in percentage, is evaluated as follows:

$$\left\{ Accuracy^{(K)}(i)\,\% = \frac{N_{i,j}^{(K)}\Big|_{j=i}}{N_i^{(TEST)}} \cdot 100 \right\}_{i=1}^{N_C} \tag{6}$$

where the superscript K stands for either crisp (C) or fuzzy (F) and $N_i^{(TEST)}$ is the total number of fruit test samples belonging to the i-th maturity category. For the crisp $Accuracy^{(C)}$, $N_{i,j}^{(C)}$ is the number of fruit test samples belonging to the i-th maturity category and assigned (1$^{\text{st}}$ rank) to the j-th category (i.e., $M_{j_1} = M_j$); the $N_C \times N_C$ matrix formed by the $N_{i,j}^{(C)}$ elements is the so-called (crisp) *confusion matrix* – the more it is close to diagonal the better. In practice, the conventional crisp $Accuracy^{(C)}$ evaluates the per-category accuracy of the crisp decision M_{j_1} provided by equation (4) while disregarding the reliability of such decision embodied by the confidence level C_{j_1} and the 2$^{\text{nd}}$ provided candidate category M_{j_2}. A more adequate accuracy measure should, instead, take into account that strict category boundaries cannot be rigorously defined and that a decision support system is provided by means of category ranking and reliability levels that warns the user towards those fruits that deserve more subtle inspection. Thus, the fuzzy $Accuracy^{(F)}$ may be considered by evaluating in equation (6) the number $N_{i,j}^{(F)}$ of fruit test samples belonging to the i-th maturity category for which, in correspondence to the retrieved FF values, the membership function μ_{M_j} of the j-th category is not null. Actually, the fuzzy $Accuracy^{(F)}$ is a more appropriate measure of accuracy in this case, because it includes among correct classifications those fruits assigned to an adjacent maturity category with a non-maximum reliability for which the correct category scored 2$^{\text{nd}}$ (i.e., those fruits for which the retrieved FF values fall within the correct trapezoidal membership function), thus incorporating the fuzziness inherent to category definition.

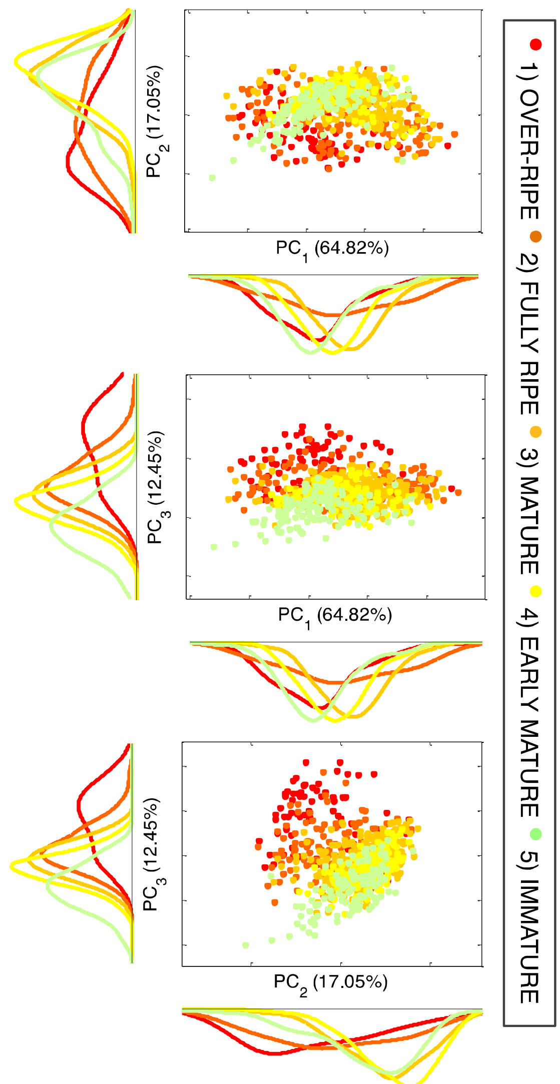

Fig. 6. PCA score plots for pairwise combinations of the first three principal components with plots of marginal histograms.

An overall accuracy (OA) performance measure can be taken by dividing the total number of test fruit samples correctly classified (either in a crisp or fuzzy sense) to the total number of test fruit samples, as follows:

$$OA^{(K)}\% = \frac{1}{\sum_{i=1}^{N_C} N_i^{(TEST)}} \sum_{i=1}^{N_C} N_{i,j}^{(K)}\Big|_{j=i} \cdot 100 \tag{7}$$

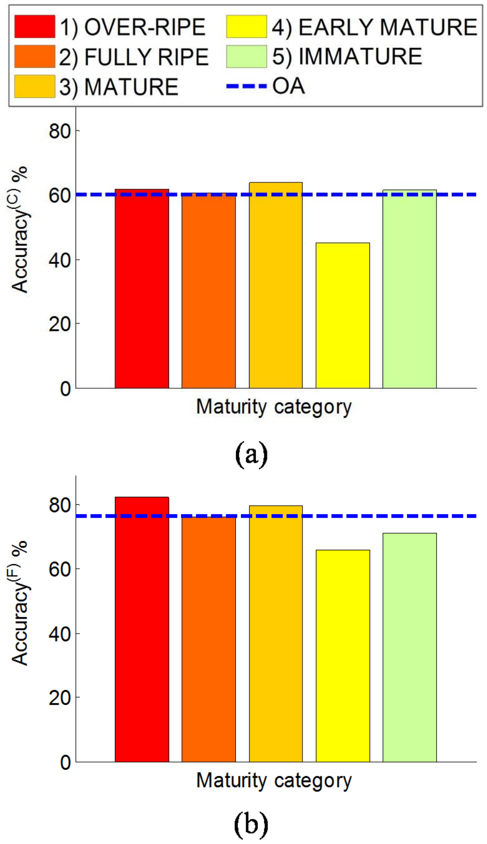

Fig. 7. Bar graphs of (a) crisp and (b) fuzzy accuracies (%).

IV. Experimental Results and Discussion

A. Preliminary Data Analysis

As a preliminary analysis, similarly to what is done in several papers from the literature of non-destructive food quality assessment [16], [22], [25], score plots obtained by principal component analysis (PCA) [4] applied to the acquired spectra were examined. These plots are reported in Fig. 6 for pairwise combinations of the first three principal components, which accounted for about 94.32% of the total data variance. The data marginal histograms are also plotted for completeness. The high overlap of the data belonging to the five maturity categories indicates that, for these data, peach fruit maturity grading is not a trivial task at all and processing techniques such PCA or linear discriminant analysis (LDA) [4] cannot work in this case.

B. FF Retrieval, Fuzzy Classification, and Maturity Grading

Intermediate FF retrieval results provided, on average, a RMSEP=1.40, which goes down to RMedSEP=0.87 when the robust-to-outliers estimator of the mean is considered. These were obtained with regression coefficients yielding $R^2 = 0.73$. These results are in compliance with values reported in the literature of fruit FF retrieval [3], [10], [11], [29], [30], [37].

Fig. 7 reports accuracy results of the fuzzy classifier application, in terms of both crisp (Fig. 7(a)) and fuzzy (Fig. 7(b)) accuracies (in percentage) computed over the test fruit samples and averaged over the three trials. The accuracies are plotted as bar graphs with respect to the maturity categories, with the corresponding OA plotted with a dashed line. As mentioned above, the crisp accuracy provides the accuracy that would result from the classifier as if the fruits were strictly classified within the maturity categories recommended by the agronomist by rigorous decision rules that completely disregard the fuzziness inherent to the process. Nonetheless, the crisp accuracy can be considered as a sort of lower bound to the actual accuracy experienced when exploiting the additional information provided by the fuzzy classifier and decision support system thereof. As is evident from Fig. 7 (a), when neglecting the information associated with decision reliability and 2nd candidate maturity category, an OA of about 60% is obtained with the crisp approach. Per-category accuracies fluctuates around 60%, with the M_1 "over-ripe", M_3 "mature", and M_5 "immature" categories being the categories with the highest accuracies and the M_2 "fully ripe" and M_4 "early mature" categories exhibiting the lowest accuracies. By inspecting the crisp confusion matrix, i.e. the matrix made up by the elements $N_{i,j}^{(C)}$ (not reported for lack of space), it is mostly tri-diagonal in all three trials with no more than 8 fruits out of 280 being responsible for no more than 5 non-null elements off the three diagonals. This means that among the fruits that were not correctly classified in a crisp sense, most of them (about 94% on average) were indeed assigned to an adjacent category. Among the peach fruits assigned to an adjacent category, some of them may actually correspond to retrieved FF values too far from the true ones, whereas others are likely to have provided retrieved FF values lying close to (but on the wrong side of) the decision boundary. By including these latters within correct classifications (in the exact terms of what explained in section III.D), the fuzziness inherent to the definition of maturity categories is accounted for and the value-added provided by category ranking and reliability levels is not neglected. This process results in the fuzzy accuracies plotted in Fig. 7 (b), which on average nearly reach 80% of accuracy. Specifically, the accuracy for M_1 "over-ripe" and M_3 "mature" categories is higher than and approximately equal to 80%, respectively, the accuracy for M_2 "fully ripe" category is higher than 75%, whereas the other categories exhibit accuracies that are around 70%. This plot means that nearly 80% of the peach fruits were correctly classified or assigned to an adjacent category with non-maximum reliability.

As a further result, an extract of the ranking and reliability chart provided to the user by the decision support system is reported in Table II as regards some of the peach fruits belonging to the M_3 "mature" category. The last column is reported in grey because the corresponding information (i.e., the true class) is not clearly provided to the user but it is reported here for convenience. As is evident, the chart offers the user a synoptic representation of the fuzzy classification outcome, by providing the user with maturity category decision, corresponding confidence level and associated reliability, and 2nd candidate category. In the example reported,

TABLE II

EXAMPLE OF RANKING TABLE WITH RELIABILITY LEVELS FOR SOME OF THE "MATURE" FRUITS (e.g., FRUITS WITH PENETROMETER MEASURED FLESH FIRMNESS LYING BETWEEN 5 AND 7 kg)

FRUIT	RANK		CONFIDENCE LEVEL		True class	μ_3
#	1st (M_{j1})	2nd (M_{j2})	1st (C_{j1})	2nd (C_{j2})		(C_3)
1	3 - MATURE	4 - EARLY MATURE	0.56	0.44	3 - MATURE	0.56
2	3 - MATURE	4 - EARLY MATURE	0.73	0.27	3 - MATURE	0.73
3	3 - MATURE	-	1	0	3 - MATURE	1
4	3 - MATURE	4 - EARLY MATURE	0.98	0.02	3 - MATURE	0.98
5	2 - FULLY RIPE	3 - MATURE	0.66	0.34	3 - MATURE	0.34
6	3 - MATURE	-	1	0	3 - MATURE	1
7	4 - EARLY MATURE	3 - MATURE	0.69	0.31	3 - MATURE	0.31
8	3 - MATURE	2 - FULLY RIPE	0.69	0.31	3 - MATURE	0.69
9	3 - MATURE	4 - EARLY MATURE	0.87	0.13	3 - MATURE	0.87
10	4 - EARLY MATURE	-	1	0	3 - MATURE	0
11	1 - OVER-RIPE	2 - FULLY RIPE	0.54	0.46	3 - MATURE	0
12	4 - EARLY MATURE	3 - MATURE	0.58	0.42	3 - MATURE	0.42
...	...	...	...	...	...	...

FRUIT MATURITY CATEGORY

- 1 – OVER-RIPE
- 2 – FULLY RIPE
- 3 – MATURE
- 4 – EARLY MATURE
- 5 – IMMATURE

RELIABILITY LEVELS

Maximum reliability	($C_{j1} = 1$)
High reliability	($0.75 \le C_{j1} < 1$)
Moderate reliability	($0.65 \le C_{j1} < 0.75$)
Low reliability	($0.5 \le C_{j1} < 0.65$)

7 fruits (i.e., fruit # {1, 2, 3, 4, 6, 8, 9}) were correctly classified also according to the crisp approach (i.e., $M_{j_1} = M_3$), with various different reliability levels; 3 fruits (i.e., fruit # {5, 7, 12}), although not correctly classified in a crisp sense (i.e., $M_{j_1} \neq M_3$), can be considered correctly classified in a fuzzy sense – in fact, they exhibit a 1st rank decision characterized by low or moderate reliability and the 2nd rank category is indeed the true one (i.e., $M_{j_2} = M_3$); 2 fruits (i.e., fruit # {10, 11}) were misclassified also in a fuzzy sense – in fact, fruit #10 was assigned to the adjacent M_4 "early mature" category with maximum reliability, whereas fruit #11 was assigned to the non-adjacent M_1 "over-ripe" category. As is evident by TABLE II, the ranking and reliability chart offers the user an immediate *snap-shot* of the situation by signaling the cases that need user intervention.

V. CONCLUSION

This work has presented an automated non-destructive peach fruit grading approach that makes use of spectroscopy-based sensors. Rather than identifying the optimal harvesting window for picking a fruit, here peach fruits are classified within several different maturity categories, ranging from immature to over-ripe fruits. A novel three-step approach is proposed where non-destructive measurements of peach fruit reflectance are carried out in the first step, fruit flesh firmness is retrieved in the second step by means of multivariate techniques, and the retrieved flesh firmness values are processed with a maturity fuzzy classifier in the third step. The user is provided with ranking of maturity categories and associated reliability levels within the framework of a decision support system that is aimed at assisting the user during the decision-making process. Classification is carried out within a decision-theory-based multiple-hypotheses testing framework and on the basis of decision rules built exploiting that maturity categories can be defined based on suitable ranges of the fruit flesh firmness values.

Experimental results performed with a peach fruit data set characterized by a high degree of maturity variability have provided a proof-of-concept of the effectiveness of the proposed approach at grading peach fruits according to their maturation stage with respect to agronomist-defined maturity categories. By coupling a flesh firmness multivariate retrieval methodology characterized by high predictive power together with an flesh firmness-based fuzzy classifier (and decision support system thereof) conceived *ad hoc* to relax maturity class boundaries, the proposed approach has been shown to correctly classify, in a fuzzy sense, about 80% of the fruits. In fact, 60% of the fruits were correctly classified even in a crisp sense (1st rank), whereas the remaining 20% were assigned to adjacent maturity categories with non-maximum reliability and the fuzzy membership function of the correct category was not null. The ranking and reliability chart provided as output has been revealed to offer the user a quick synoptic view of the classification outcome useful to assist the user in the decision-making process by identifying those fruits that deserve further inspection.

The overall approach has been shown to have great potential in industrial and horticultural applications for the realization of easy-to-use automated maturity grading systems to be employed by non-expert users directly in the orchard or in the warehouse. In the future, the approach will be extended to the use of *imaging* spectroscopic sensors (hyperspectral imaging sensors), in order to improve maturity grading performance by benefiting of the multiple features provided by exploitation of spatial information.

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