DETECTION OF INTERNAL QUALITY IN KIWI WITH TIME-DOMAIN DIFFUSE REFLECTANCE SPECTROSCOPY

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ABSTRACT. *Time-domain diffuse reflectance spectroscopy (TRS), a medical sensing technique, was used to evaluate internal kiwi fruit quality. The application of this pulsed laser spectroscopic technique was studied as a new, possible non-destructive, method to detect optically different quality parameters: firmness, sugar content, and acidity. The main difference with other spectroscopic techniques is that TRS estimates separately and at the same time absorbed light and scattering inside the sample, at each wavelength, allowing simultaneous estimations of firmness and chemical contents. Standard tests (flesh puncture, compression with ball, °Brix, total acidity, skin color) have been used as references to build estimative models, using a multivariate statistical approach. Classification functions of the fruits into three groups achieved a performance of 75% correctly classified fruits for firmness, 60% for sugar content, and 97% for acidity. Results demonstrate good potential for this technique to be used in the development of new sensors for non-destructive quality assessment.*

Keywords. *Optical properties, Time-domain diffuse reflectance spectroscopy (TRS), Laser, Firmness, Sugar, Acidity, Models.*

Among other non-destructive sensing techniques, optical methods of analysis have been studied for many years considering their potential to measure internal properties of foods (Gunasekaran et al., 1985; Skoog et al., 1998; Abbott, 1999). Historically, near-infrared (NIR) spectroscopy is known by its applicability for the internal quantification of compounds. NIR techniques have been widely used to non-destructively measure acidity and soluble solid internal content: for example, Bellon-Maurel et al. (1997) developed a fast NIR sensor to measure sugar in apples; Ventura et al. (1998) determined soluble solids in apples with NIR; Slaughter (1995) applied infrared spectroscopy to peaches, for the quantification of soluble solids, and diverse specific sugars; Miyamoto et al. (1998) quantified acid content of satsumas with infrared transmittance. Research has been done in estimating firmness and soluble solids of apples with infrared spectroscopy (Choi et al., 1997; Lammertyn et al., 1998), as well as firmness, dry matter, and soluble solids of kiwi fruits (McGlone and Kawano, 1998), identifying specific wavelength ranges for each attribute.

Regarding the application of lasers as light sources, Tu et al. (1995) uses a He-Ne laser to light tomato and apple; the dispersed light is recorded by an image acquisition system and the number of pixels, after an image segmentation process, was correlated with firmness (stiffness factor, obtained by means of acoustic response). The same research team studied the effect of apple turgidity on the reflection of an incident laser beam, as an indicator of fruit ripeness. Two red lasers were applied on the samples, and the reflection image was acquired with a camera. Correlations were low compared with color L.a.b. standard measurements and acoustic response (De Belie et al., 1999).

McGlone et al. (1997) also applied an 864-nm laser source on kiwis to search for relations between fruit optical response and firmness. In this work, the laser beam was focused on a rotating fruit piece, and the overall scattered light was measured with a silicon detector, at the same time another detector was used to track the reference signal. Consistent correlations were found between the intensity of the scattered light and the penetrometry firmness measurement. The same author used a different laser technique to estimate fruit firmness: delivering a puff of air on to the fruit surface resulted in a local deformation (proportional to sample firmness), which can be measured using a laser displacement sensor (McGlone et al., 1999). Hung et al., 1999) developed a similar air-puff device, with similar results.

Duprat et al. (1995) created an artificial vision system based on a laser light source, for non-destructive estimation of firmness of Golden apples. Using a 670-nm diode, a stereomicroscope, and a camera, it was found that the illuminated area was broader in firmer fruits; thus, good correlation was established between the processed image size and Young modulus. Han and Lambert (1998) also used image acquisition devices to grab pictures of laser-lighted apples. After illuminating with 632-, 685-, and 769-nm lasers, the image was processed and thresholded, and the results were used to classify apples in four firmness categories. The reference measurement for firmness was Magness-Taylor penetrometry.

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All the previously mentioned works make use of the laser properties (highly collimated beam, high power, monochromatic) applied to firmness estimation, taking advantage of the spatial dispersion of the light when it crosses a tissue. However, there was no direct quantification of the scattering level: only the attenuation of the light, or just the recovered light intensity is registered. Moreover, none of the studies was intended to simultaneously measure firmness and internal compounds, such as soluble content and acidity.

Time-domain diffuse reflectance spectroscopy (TRS) is an optical technique developed for medical applications and related areas (Cubeddu et al., 1994a). It has potential as a new technique for agricultural and food industry applications. TRS is useful, for example, to quantify photosensitive dyes injected to*in vivo* tissues, to locate tumors due to the differential optical properties of their tissues (Cubeddu et al., 1994b). TRS provides a complete optical characterization of a diffusive sample as it estimates at the same time, and independently, the light absorption inside the tissues and the scattering across them. Light sources are pulsed lasers emitting in a single wavelength or tunable. Light is pumped into the sample at a very short pulse rate. The working principle of the technique is the analysis of the attenuation and broadening of the time-distribution of the re-emitted light, and the correct interpretation with a proper theoretical model. TRS, unlike the previously mentioned optical techniques using laser, is capable of registering a time signal of the reemitted light (fig. 1) by means of a photo-counting sensor and a time-acquisition board. After applying the light diffusion theory (Cubeddu et al., 1994a), a de-convolution signal is obtained, and two coefficients are calculated: absorption coefficient (μ_a) and transport scattering coefficient (μ'_s). Our hypothesis was that light absorption could be correlated with soluble solid content or acidity (especially in the NIR region), and the scattering coefficient could be useful to estimate firmness, at the same time. The physical-chemical basis behind this hypothesis is that specific molecules will absorb luminous energy (VIS, in the case of chlorophyll pigments; molecular vibration in the case of NIR absorption) affecting the absorption coefficient (μ_a), while intracellular and tissue microstructures (cell organelles, starch granules, cell wall, intercellular spaces) will cause internal light reflections, diffractions, and spatial dispersions to the photons, affecting their light pathway and, thus, the transport scattering coefficient (μ'_s).

TRS will provide simultaneous information on chemical composition and rheology of the tissues, which is a main advantage compared to other traditional spectroscopic techniques (capable only to register the global attenuation spectrum) and offers opportunities for applying this new measurement method in the food industry.

The objective of this research was to study the applicability of TRS to the non-destructive detection of internal physical properties (firmness) and chemical composition (soluble solids content and acidity) simultaneously, on kiwi fruits.

Materials and Methods

A total of 180 kiwi fruits were measured during two sampling phases (July 97 and February 98) along the collaborative test periods between two of the partners of this EU research project, Universidad Politécnica Madrid (UPM) and Politecnico di Milano (INFM). Samples with diverse ripeness stages ('Hayward' variety) were acquired in Italian local markets. In order to facilitate data management and analysis, samples were initially grouped into "batches" numbered as K1 to K9. Each batch was conformed to 20 fruits of uniform ripeness (visual - tactile estimation, subjective), and a minimum of two batches (one "ripe" and another "unripe") was measured per day.

On each sample, a laboratory TRS system was applied on both sides of the samples to (non-destructively) measure their optical response under sequential illumination with two tunable VIS and NIR lasers, in the wavelength range 610 to 1010 nm. Absorption and transport scattering coefficients for each wavelength were calculated later, after signal processing. Diffuse reflected spectra of the kiwis were acquired in the time domain. De-convolution of the signal (fig. 1) was applied to extract the internal optical parameters from the data curve: absorption coefficient (μ_a) and transport scattering coefficient (μ'_s). The system and methodology is described in detail in Cubeddu et al. (2001). Repetition of this procedure on the same acquisition point for each laser wavelength leads to an absorption spectrum (fig. 2) and a scattering spectrum of the sample. The absorption spectrum offers a similar pattern as if it was acquired with a traditional spectroscopic technique. Notation for TRS variables used in this study was the following: 'MA600' to 'MA1000' denote absorption coefficient, μ_a, at each wavelength (600 to 1000 nm), while 'MS600' to 'MS1000' stand for scattering coefficient, μ'_s, at each wavelength (see notation table at the end of this section).

External color of the samples was measured using a Minolta CM-508i spectrometer (Minolta Co., Ltd., Osaka, Japan). Spectra in the VIS region (400 to 700 nm) were registered on the skin, and used in the later analyses as an indicator of the overall pigmentation of the samples external color. Variables 'C400' to 'C700' (reflection intensity at each wavelength) were used in the analyses.

Destructive tests (mechanical and chemical) were then used as reference measurements for firmness, acidity, and

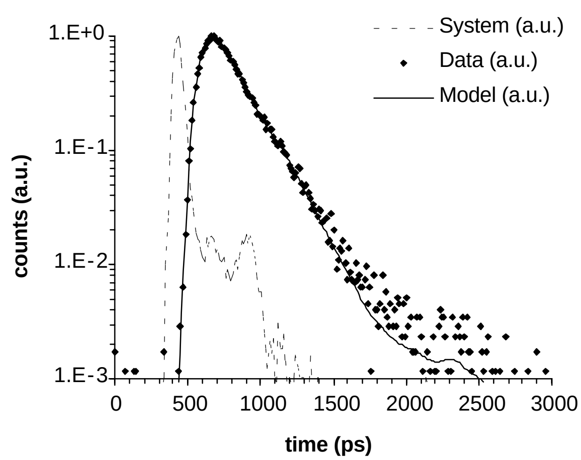

Figure 1. Data points (diamonds) acquired with TRS on an intact fruit, lighting with a 970-nm laser. System function response (dashed line) and curve fitted to data (solid line) using the diffusion theory are also shown. Units are picoseconds for the time axis, and arbitrary units (a.u.) for the vertical axis, proportional to the number of photons counted by the detector (extracted from Cubbedu et al., 1999a).

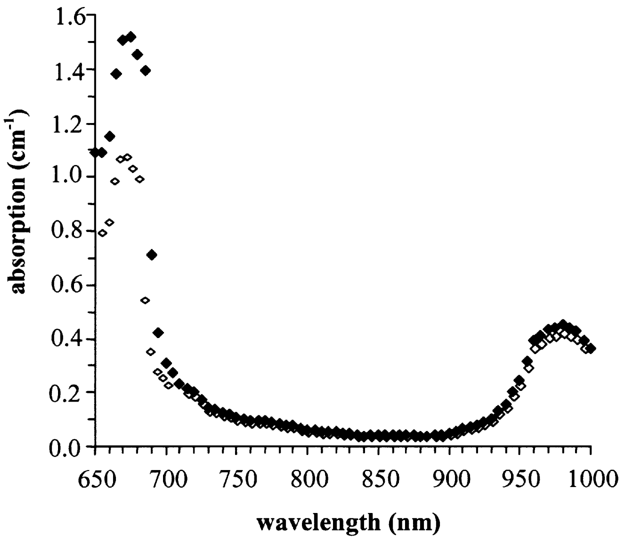

Figure 2. Absorption spectrum of a high maturity (empty points) kiwi and a low maturity one (solid points) (Cubbedu et al., 1999b).

soluble solid content. The mechanical tests for the determination of firmness were:

• Puncture of fruits with a needle: was carried out with a texture analyzer machine (Stable Micro Systems Ltd., model TAXT2, Surrey, UK) with a cylindrical probe of 0.8-mm diameter and flat base. The probe was applied on the skin at 20-mm/min speed rate; the test stopped at 8 mm of depth. Deformation was immediately removed at the same speed rate. One measurement was made per side of each fruit and then was averaged. The following parameters were registered maximum force (N, notation as ‘PF1’), which is related to skin resistance and ratio force/deformation (N/mm, ‘PG’), an indicator of turgidity (i.e. firmness of outer tissues).

• Quasi-static compression with a sphere was performed with the texture analyzer by compressing each fruit on the skin with a 19.5-mm diameter steel ball. It was done at a speed rate of 20 mm/min and stopped when 3 mm of deformation was reached. Two measurements were performed on each fruit, one per side, and averaged. Registered parameters were maximum force (N, ‘BF1’) related to flesh firmness and ratio force/deformation (N/mm, ‘BFD1’) related to Young’s modulus.

Chemical tests were also conducted on the samples:

• Titration of total acid content. After extracting the juice from each side of the fruit with a squeezer, a known volume was filtrated and titrated with a solution of 0,1N sodium hydroxide until pH = 8.2 was reached. An automatic titrator was used (model TR85-T80, Schott-Gerate GmbH, Hofheim, Germany). The milliequivalents of acid concentration were calculated for each sample side and averaged for each fruit.

• Refractometric index. Brix degrees (soluble solids content, SSC) of both fruit sides were measured on the juice of the samples using a digital, temperature-compensated refractometer (model PR-101, Atago Co. Ltd., Tokyo, Japan) and then averaged. Refractometric index was used as an indicator of sugar content of the fruits.

• Principal Component Analysis (PCA): to find which TRS coefficients, and at which wavelengths, were best correlated with the diverse quality parameters.

Notation of variables used in the analysis.

Variables	Meaning	Variables	Meaning
MA600 ...MA1000	TRS absorption coefficient, μa, at each wavelength (600 – 1000 nm)	BFD1	Ratio max force/deformation (slope) during compression with ball test, N/mm
MS600 ...MS1000	TRS transport scattering coefficient, μ’s, at each wavelength (600 – 1000 nm)	SUGAR	Soluble solid content, °Brix
C400 ... C700	VIS reflectance, % at indicated wavelength (400 to 700nm), skin color	ACID	Total acidity of squeezed juice, meq/l
PF1	Max force during puncture with needle test, N	DAY	Day of measurement
PG	Gradient (slope) of the curve during puncture with needle test, N/mm	FRUITN	Fruit number inside batch
BF1	Max force during compression with ball test, N	BATCH	Code of fruit batch (K1 to K9)

• Multiple Stepwise Linear Regression (MLR): to develop continuous estimation models for firmness, acidity or SSC.

• Clustering techniques and Discriminant Analysis (DA): Cluster analysis was used to “naturally group” fruits according to their internal quality, measured with the reference tests. Discriminant analysis was used to create classification models with the TRS coefficients as the explicative variables. The basic idea underlying discriminant function analysis is to determine whether groups differ with regard to the mean of a variable, and then to use that variable to predict group membership (e.g., of new cases). In our case, we provided to the software, in a first approach, all the available TRS variables, leaving for the computations the decision on choosing the ones with highest significance. In the forward stepwise discriminant function analysis, a model of discrimination was built step-by-step. Specifically, at each step all variables are reviewed and evaluated to determine which one will contribute most to the discrimination between groups. That variable was then included in the model, and the process started again.

To create the classification models, the individual fruits first was grouped into clusters according to the reference test that was going to be estimated (i.e., firmness, or soluble solid content, or acidity), and then the model function itself was created using the TRS coefficients to classify the samples into groups of high, medium and low firmness (or high, medium, and low sugars or high, medium, and low acids). This methodology was used for all the samples, building a set of clusters for each quality attribute independently (firmness, sugars, and acids), using only one factor (reference variable extracted from the destructive tests) in each cluster analysis. Slope of the curve during puncture with needle test (‘PG’, N/mm) was used to create firmness clusters, refractometric index (°Brix) was used for sugar clusters, and total acidity (meq/l) for acidity clusters. To build up these sets, the k-means clustering method was used, which produces exactly k different clusters of the greatest possible distinction. In this work k = 3 clusters were established for each quality parameter, representing high, medium, and low levels. This number of clusters was thought to be useful for fruit industry purposes, where a higher level of classes will complicate fruit sorting and packaging.

Once the fruits were distributed into sets of quality clusters, the next step was trying to estimate –to reproduce– those clusters using the optical TRS information contained in the μ_a and μ'_s parameters ('MA' and 'MS' variables); the discriminant analysis technique was used for this objective.

Different models were built for each quality parameter. To create the classification function models, a learning subset consisting of 50% of the fruit of the database was used. Models were then validated using the other half of the database. Several cross validations were made also combining different subsets of the database. The scattering and absorption variables in the VIS region were used to build the models for firmness estimation, and the TRS variables in the NIR area were used as explanatory variables in all models.

Results

Initial Correlation Between TRS and Reference Tests

With all the destructive and non-destructive data together, principal component analysis was performed to search for links among optical TRS data and reference tests to find which TRS variables were best correlated with firmness, acidity, or soluble solids. From the PCA plot (fig. 3) it can be seen that some initial correlation was observed between the scattering coefficients at different wavelengths and the firmness destructive variables. The closer to an axis a variable is, the higher its correlations with other variables next to the axis; the closer to the external circumference (the "correlation circle"), the higher the correlation coefficient. This finding was especially true in the case of the scattering coefficient at 750 and 800 nm ('MS750,' 'MS800') and some textural variables, such as the gradient of the puncture test through the skin ('PG'), maximum force registered in puncture test ('PF1') and maximum force in compression with ball test ('BF1'). This observation is evidenced from the grouping of these variables into Factor 1 (first principal component, horizontal axis). This factor also has some information about the accessory variables "day of measurement" and "number of batch," suggesting that the conformation of the batches on each measurement day was not homogeneous. In the vertical axis, only the TRS absorption coefficient at 675 nm ('MA675') and skin reflectance at the same wavelength had stronger correlations, which are the "green level" of the samples (chlorophyll absorption's peak rises at 680 nm), as an indicator of their ripening stage. Acidity ('ACID') and soluble solids content ('SUGAR') are not clearly correlated with any other variable in this projection of the PCA results.

In a second approach, three batches were selected (K5, K7, and K9) with the aim of feeding the analysis with extreme conditions in order to set up relations more clearly. These three batches had high, medium, and low firmness, but medium, high, and low contents in acids and sugar, respectively (fig. 4). In this way, the results allow segregation of the effect of firmness from the chemical composition, and they will not be biased by crossed interactions. With the

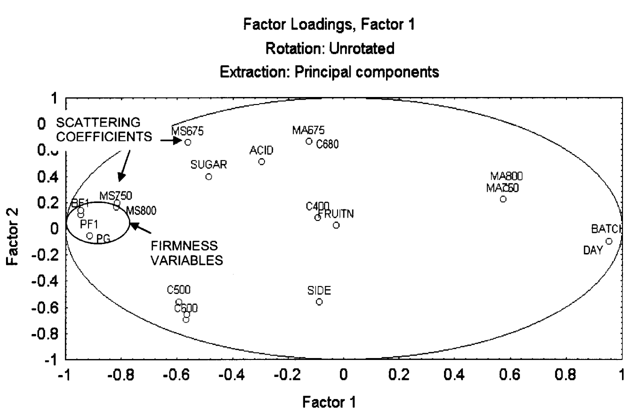

Figure 3. Principal components analysis plot using all the acquired data (n = 180 samples). Variables extracted from the destructive and non-destructive are represented in a space formed by Factor 1 and Factor 2 of the PCA result. Variable codes are explained in the notation table.

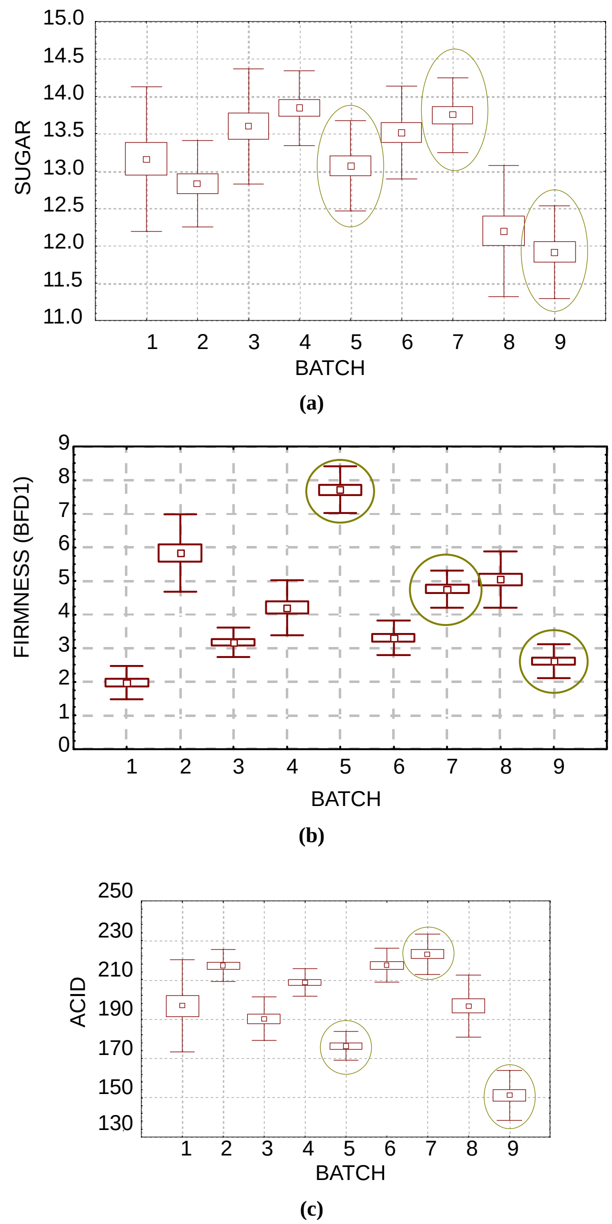

Figure 4. Quality ranges of kiwi batches according to soluble solids content (a; °Brix), firmness level (b; ratio force/deformation in compression w/ball) and acidity (c; meq/l): groups no 5, 7, and 9 (marked) were selected to build MLR models, from the whole database of nine batches.

Table 1. Second PCA with three selected batches of kiwi.[a]

Kiwi
Principal Components Analysis
Batches 5, 7, and 9 only (n = 60)

Variables		Factor 1	Factor 2
Color (VIS reft%)	C400	-0.092	0.077
	C500	-0.592	-0.562
	C600	-0.565	*-0.698
	C680	-0.564	*-0.658
firmness (compr w/ball and puncture)	BF1	*-0.946	0.103
	BFD1	*-0.947	0.105
	PF1	*-0.914	-0.060
	PG	*-0.945	0.136
TRS Absorption and scattering	MA675	-0.125	*0.658
	MA750	0.575	0.218
	MA800	0.587	0.304
	MS675	-0.562	*0.654
	MS750	*-0.818	0.158
	MS800	*-0.816	0.194
Acid		-0.294	0.504
Sugar		-0.486	0.394
Batch		*0.953	-0.099
Side		-0.085	-0.566
Fruit		-0.027	0.019
Explained variance		8.096	3.089
Expl. var. %		42.6%	0.16%

[a] Numbers (factor scores) are equivalent to correlation coefficients between quality parameters and PCA factors. Correlations over 0.6 are highlighted (*).

measurements from these batches, a new PCA (table 1) was performed, which produced clear correlation between firmness ('BF1,' 'BFD1,' 'PF1,' 'PG') and scattering at 750 and 800 nm ('MS750,' 'MS800'), as is demonstrated by their corresponding factor scores (>0.85), which can be understood as correlation coefficients between the respective variables and the Factor grouping them. This result allowed the creation of linear estimation models with greater correlation levels. Some correlation was shown also in the PCA between the VIS external reflectance around the chlorophyll peak (vars. 'C600,' 'C680') and the TRS information at similar wavelengths ('MA675,' 'MS675;' see correlation coefficients at table 1, factor 2)

Continuous Estimation Models

Different Multiple Stepwise Linear Regression (MLR) models were created (table 2) to predict firmness (ratio force/deformation with ball, 'BFD1') using the TRS variables. The regression models (table 2) were better when combining scattering and absorption variables ($R^2 = 0.8$) than when including only scattering ($R^2 = 0.6$). Nevertheless, models performance was lower than expected (especially for chemical estimation, not shown), and a new approach, building of non-continuous estimation models to classify the samples into categories, was followed.

Classification Models

Classification results are presented in classification matrix tables for each one of the created models, indicating in rows the composition of the clusters, the classification scores for each one, as well as the mean value of the estimated quality attribute (firmness, °Brix, or acids). In columns, the predicted "groups" are shown, formed by the model trying to match the true clusters. Results were as follows:

- 75% of the fruits were correctly classified into three firmness classes using MS and MA of three VIS wavelengths to estimate ratio force/deformation of puncture test ('PG,' table 3); validation with part of the database not used to build the model obtained 74% of well classified fruits (wcf) (table 4). Figure 5 shows the true mean firmness values for each cluster.
- 97% of the fruits were correctly classified into three acidity levels using μ_s and μ_a of 10 NIR wavelengths to estimate meq/l (table 5); the validation achieved 77% of wcf (table 6). Figure 6 shows the true mean acidity values for each cluster.
- 60% of the fruits were correctly classified into three soluble solids classes using μ'_s and μ_a of eight NIR wave

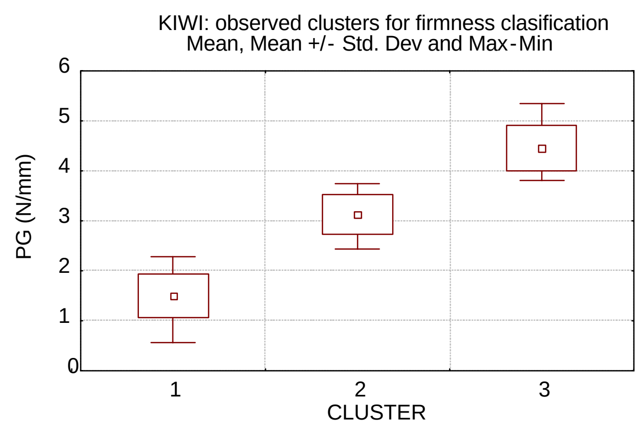

Figure 5. Mean values and ranges of clusters (observed categories) used to build the kiwi fruit classification model into three firmness levels ('PG' estimation).

Table 2. Multiple linear regression models using TRS absorption and scattering coefficients to estimate firmness (left), or using only scattering (right). Data used included only selected batches of kiwi (K5, K7, and K 9), n = 60.

KIWI MLR model estimating firmness using Scattering + Absorption
Regression Summary for Dependent Variable: BFD1
Adjusted R^2 = 0.81423321
F(5.54) = 52.721 p < 0.00000
Std. Error of estimate: 0.94378

	B	St. Err. of B	t(54)	p-level
Intercept	12.118	4.338	2.794	0.007
MS750	1.658	0.243	6.813	0.000
MA750	-96.457	29.605	-3.258	0.002
MA675	-51.603	10.977	-4.701	0.000
MS675	2.877	0.665	4.327	0.000
MA800	41.897	33.462	1.252	0.216

KIWI MLR model estimating firmness using ONLY SCATTERING
Regression Summary for Dependent Variable: BFD1
Adjusted R^2 = 0.60549812
F(2.57) = 46.278 p < 0.00000
Std. Error of estimate: 1.3753

	B	St. Err. of B	t(57)	p-level
Intercept	-13.691	3.377	-4.055	0.000
MS750	2.157	0.316	6.828	0.000
MS675	0.873	0.645	1.353	0.181

Table 3. Classification matrix for firmness estimation (‘PG’ variable, N/mm) using TRS coefficients in the VIS region.[a]

Kiwi Firmness	Well Classified (%)	Group 1 p = 0.52941	Group 2 p = 0.24706	Group 3 p = 0.22353	Mean PG for each Cluster (N/mm)
Cluster 1	97.7	44	1	0	1.4
Cluster 2	14.2	9	3	9	3.1
Cluster 3	89.4	2	0	17	4.4
Total	75.3	55	4	26	n = 0

[a] Rows: “observed” clusters. Columns: “estimated” group ascription. Last column: mean actual firmness values for each cluster.

Table 4. Validation matrix for firmness estimation (‘PG’ variable, N/mm) using TRS coefficients in the VIS region.[a]

Kiwi Firmness Validation	Well Classified (%)	Group 1 p = 0.52941	Group 2 p = 0.24706	Group 3 p = 0.22353	Mean PG for each Cluster (N/mm)
Cluster 1	93.7	45	1	2	1.4
Cluster 2	10.0	8	2	10	3.1
Cluster 3	94.1	1	0	16	4.4
Total	74.1	54	3	28	n = 0

[a] Rows: “observed” clusters. Columns: “estimated” group ascription. Last column: mean actual firmness values for each cluster. Validation was performed with the part of the database not used for learning purposes.

lengths to estimate °Brix (table 7); validation scored 62% of wcf (table 8). Figure 7 shows the true mean SSC values for each cluster.

Discussion

The acquisition of non-homogeneous, market-sold samples was shown to be an efficient way of providing samples to screen the TRS data for the estimation of kiwi fruit internal quality because wide ranges of quality parameters can be achieved easily. To calibrate the technique and the models, in terms of validation, adjustment, repeatability, etc., more controlled samples can be used to enhance the results.

PCA results demonstrate that TRS scattering coefficients are strongly correlated with destructive firmness measurements. No evidence of the relation between absorption coefficients and chemical composition was observed in

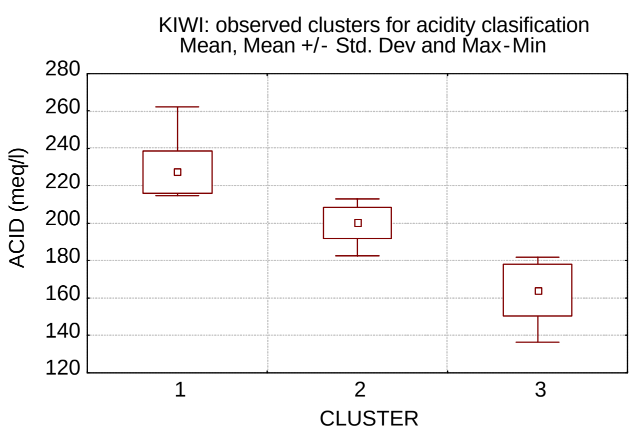

Figure 6. Mean values and ranges of clusters (observed categories) used to build the kiwi fruit classification model into three acidity levels (‘ACID’ estimation).

Table 5. Classification matrix for acidity estimation (‘ACID,’ meq/l) using TRS coefficients in the NIR region.[a]

Kiwi Acidity	Well Classified (%)	Group 1 p = 0.45000	Group 2 p = 0.48750	Group 3 p = 0.06250	Mean Acid for each Cluster (meq/l)
Cluster 1	100	19	0	0	227.3
Cluster 2	100	0	16	0	200.1
Cluster 3	80.0	0	1	4	164.1
Total	97.5	19	17	4	n = 0

[a] Rows: “observed” clusters. Columns: “estimated” group ascription. Last column: mean actual acidity values for each cluster.

Table 6. Validation matrix for acidity estimation (‘ACID,’ meq/l) using TRS coefficients in the NIR region.[a]

Kiwi Acidity Validation	Well Classified (%)	Group 1 p = 0.47500	Group 2 p = 0.40000	Group 3 p = 0.12500	Mean ACID for each Cluster (meq/l)
Cluster 1	88.2	15	0	2	227.3
Cluster 2	0	0	0	0	200.1
Cluster 3	69.5	4	3	16	164.1
Total	77.5	19	3	18	n = 40

[a] Rows: “observed” clusters. Columns: “estimated” group ascription. Last column: mean actual acidity values for each cluster. Validation was performed with the part of the database not used for learning purposes.

the PCA, but later SSC/acidity estimation models showed substantial correlation. If an adequate data analysis is performed, correlations seem to be good enough, *a priori*, to build continuous estimation models with low errors of estimation. In other cases the correlation is lower so the work should be focused towards classification models (non-continuous estimation).

Linear estimation models showed lower performance than expected, especially for SSC and acidity estimation. Firmness estimation could be achieved using a MLR function with $R^2 = 0.8$.

Classification models sorting kiwis into three classes of firmness, three classes of SSC, and three classes of acidity level, showed good scores of well classified samples for the case of acidity, and lower for firmness and SSC estimation. This result could be due to the fact that the acidity range of the samples was broader than SSC or firmness ranges.

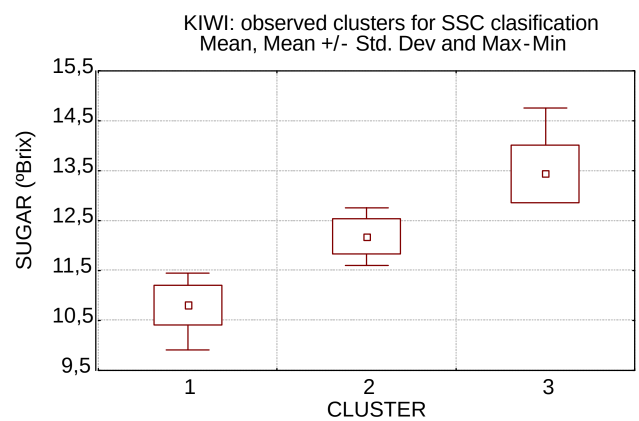

Figure 7. Mean values and ranges of clusters (observed categories) used to build the kiwi fruit classification model into three SSC levels (‘SUGAR’ estimation).

Table 7. Classification matrix for soluble solids estimation ('SUGAR,' °Brix) using TRS coefficients in the NIR region.[a]

Kiwi SSC	Well Classified (%)	Group 1 p = 0.10000	Group 2 p = 0.36250	Group 3 p = 0.53750	Mean SSC for each Cluster (°Brix)
Cluster 1	25.0	1	1	2	12.1
Cluster 2	77.27	2	17	3	13.3
Cluster 3	42.8	1	7	6	14.4
Total	60.0	4	25	11	n = 0

[a] Rows: "observed" clusters. Columns: "estimated" group ascription. Last column: mean actual SSC values for each cluster.

Table 8. Validation matrix for SSC estimation ('SUGAR,' °Brix) using TRS coefficients in the NIR region.[a]

Kiwi SSC Validation	Well Classified (%)	Group 1 p = 0.10000	Group 2 p = 0.35000	Group 3 p = 0.55000	Mean SSC for each Cluster (°Brix)
Cluster 1	25.0	1	1	2	12.1
Cluster 2	46.6	1	7	7	13.3
Cluster 3	80.9	1	3	17	14.4
Total	62.5	3	11	26	n = 0

[a] Rows: "observed" clusters. Columns: "estimated" group ascription. Last column: mean actual SSC values for each cluster. Validation was performed with the part of the database not used for learning purposes.

The estimation models included TRS variables from different wavelengths. With the present system setup, the acquisition of signal using several wavelengths needs manual tuning of lasers and minor adjustments. If a future simplified prototype is built for industrial application, this problem has to be solved designing an automatic system to change the wavelength. This will increase its price, and fabrication complexity as well as the measurement process. With the estimation models built to date, the possibility of using only one wavelength is not worthwhile because the estimation error will be too high.

It has been observed that estimation models for firmness are slightly better when introducing scattering and absorption coefficients, rather than only scattering, despite of the hypothesis that scattering was the main source of information related to firmness. This may be due to some complementary effect of absorption and scattering. On the other hand, models with both absorption and scattering variables, and a large number of wavelengths, could lack robustness (be unstable) in future validations. For future studies, the development of models only with scattering is proposed.

Conclusion

With the data collected in the VIS and NIR range and the analysis carried out, links between the TRS coefficients and fruit quality properties were found and different estimation models were created for the non destructive assessment of firmness, sugar, and acids in kiwis. Classification models provided percentages of correctly classified firmness, sugar and acids of 75%, 60%, and 97%, respectively. This agrees with the original hypothesis, in which the scattering coefficients should be related to texture properties, while the absorption should be associated with chemical compounds. So is shown by the certain correlation between scattering values in the far-visible region (750 and 800 nm) and several kiwifruit firmness variables, as well as the correlation between absorption values of NIR wavelengths and °Brix and acidity. Further research must be undertaken to acquire a better knowledge of this new optical equipment, optimize the models, and develop the commercial potential of the technique.

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