Food and Bioprocess Technology (2024) 17:205–216
https://doi.org/10.1007/s11947-023-03123-z

RESEARCH

Data from Chewing and Swallowing Processes as a Fingerprint for Characterizing Textural Food Product Properties

Raúl Grau[1,3] · Alberto J. Pérez[2] · Sergio Hernández[1] · José M. Barat[1] · Pau Talens[1] · Samuel Verdú[1]

Received: 2 March 2023 / Accepted: 5 May 2023 / Published online: 30 May 2023

Abstract

Eating is a complex action. When it is performed, lots of facial movements that depend on food and consumer characteristics take place. Several techniques and methodologies are available to evaluate them, and some are used to describe food texture. Employing facial skin markers and direct descriptors, and studying the tracking of their movements during the eating process are a simple non-invasive technique, but with limitations. This study aimed to use the technique and compare two data processes using direct or indirect descriptors to minimize limitations (panelist effect) and to increase its ability to classify muffins, coffee cookies, and toasted bread according to the descriptions provided by textural techniques. Eight participants (four men, four women) ate the three products 5 times over a 2-week period. Six skin markers were placed on certain points of their faces. Chewing and swallowing were characterized by applying the technique. The panelist effect was evidenced by employing direct descriptors, while products were described in the same way as using textural techniques by indirect descriptors.

Keywords Skin markers · Chewing · Swallowing · Food texture · Oral food processing

Introduction

Chewing and swallowing involve complex behaviors associated with the volitional and reflexive activities of more than 30 nerves and muscles (Matsuo & Palmer, 2009). While chewing, cyclic jaw movement during processes is closely coordinated with tongue, cheek, soft palate, and hyoid bone movements. While swallowing, different movements take place in the soft palatal walls of the pharynx, tongue, hyoid bone, larynx, suprahyoid and thyrohyoid muscles, and the epiglottis (Matsuo & Palmer, 2009). Thus, chewing and swallowing involve a large number of body components in motion, moved mainly by the most important muscles for this purpose: temporal (anterior and posterior), masseter (superficial and deep), medial pterygoid, lateral pterygoid (superior and inferior), and digastric muscles. However, eating involves far more muscles (Koolstra, 2002).

All these movements depend on food characteristics. Physical, chemical, rheological, and mechanical food properties substantially determine oral processing behavior (Ketel et al., 2019). During oral processing, food products undergo major and dynamic transformations (Panouillé et al., 2016) that provide texture perception changes throughout the oral processing time because food is broken down by chewing and is lubricated by saliva incorporation (Devezeaux de Lavergne et al., 2015). Oral processing movements also depend on consumer characteristics, such as age, gender, and ethnicity (Bartkiene et al., 2019; Ketel et al., 2019; Kostyra et al., 2016).

Several techniques and methodologies can be applied to evaluate chewing and swallowing, and some are used to be related to food texture. The main studied techniques are videofluoroscopy, endoscopy, computed tomography, ultrasound, electromagnetic articulography, electromyography, manometry, and electropalatography (Álvarez et al., 2019), but they are very expensive, and some are even invasive and interfere with the sensory experience. Employing skin surface markers to track the movement of the chin or other facial

✉ Raúl Grau
rgraume@tal.upv.es

1 Departamento Tecnología de Alimentos, Universitat Politècnica de València, Camino de Vera s/n, 46022 Valencia, Spain

2 Departamento de Informática de Sistemas y Computadores, Universitat Politècnica de València, Valencia, Spain

3 Universitat Politècnica de València, Ciudad Politécnica de La Innovación, Edificio 8E - Acceso F – Planta 0, Camino de Vera, s/n, 46022 Valencia, Spain

features involved in jaw movement is another technique. The 3D reconstruction of jaw movement is possible by combining a simple camera and a mirror, or by using many cameras. Unlike the previous techniques, this one is simpler (speedier setup), less invasive, and cheaper (Wilson et al., 2016), but sacrifices accuracy because of the differences in displacement between the skin and the chin, jaw, teeth, etc.

The studies that employ these techniques and methodologies normally focus on obtaining direct descriptors from the tracking of chewing and swallowing or muscle response. Descriptors like time to chew, chewing cycles, frequency, swallowing time, and tongue movements, among others, are the most widely studied (Le Révérend et al., 2016; Remijn et al., 2016; Rivera et al., 2020; Wilson et al., 2016). To develop descriptors, not all the data obtained during tests are used. Only some data are selected, transformed into descriptors, and studied with traditional statistical tools. The information skew could be the reason for the wide within-subject variability between sessions that Remijn et al. (2016) observed and Sodhi et al. (2019) described, which reduces the use of the proposed methodology to characterize foods.

Other data processing can be done by using multivariate statistical tools. With these tools, facial movement tracking can be utilized as indirect descriptors, and a fingerprint that describes food can be developed by isolating it from the panelist factor. The development of this technology can help to describe food by taking into account its interaction with the mouth, teeth, saliva, etc., and to do so dynamically: that is to say, taking into account the transformation that food undergoes during oral processing. The results could be interesting for the food industry because, among others, foods could be developed based on consumer perceptions noted while eating them. Nowadays, descriptions are done by sensory characterization employing panelists, usually consumers, who describe foods subjectively according to their perception (Forker et al., 2012; Waglay & Karboune, 2020; Monnet et al., 2022; Espert et al., 2023) because to create and to maintain well-trained and calibrated sensory panels can be economically challenging and time consuming (Cardoso et al., 2022). With the proposed technique, the description could be objective, obtaining quantified results and reducing the number of panelists without the accuracy lost.

Some other multivariate statistical tools, such as principal component analysis (PCA) and partial least squares-discriminant analysis (PLS-DA), are widely used in food statistical analyses (Granato et al., 2018; Lee et al., 2018; Verdú et al., 2019a, b, 2020, 2021). PCA is a multivariate unsupervised statistical method applied to describe and reduce the dimensionality of a large set of quantitative variables to a few new variables called principal components (PCs), which are the result of linear combinations of the original variables (Verdú, et al., 2019a). PLS-DA is a versatile algorithm that can be used for predictive and descriptive modeling, and also for discriminative variable selection. PLS-DA combines dimensionality reduction and the discriminant analysis in one algorithm, and is especially applicable for modeling high-dimensional (HD) data (Lee et al., 2018). In some cases, like when a multivariant analysis is applied, the selectivity in variables is insufficient to easily certain aspects like backgrounds or other signals that interfere with a multivariate model. In these cases, using multivariate filtering methods before model calibration (pretreatment data methods) can help to simplify the end model. Multivariate filters identify some undesirable covariance structures (i.e., how variables change together) and remove these sources of variance from data prior to calibration or prediction. Among others, generalized least squares weighting (GLSW) is a “multivariate filters” method that identifies patterns in the variables of data that should be downweighted or removed (Wise et al., 2006).

This study aimed to evaluate data from tracking facial movements during chewing and swallowing processes by employing skin surface markers as a fingerprint to characterize textural food product properties. For this purpose, two different data processes are proposed depending on the use of direct or indirect descriptors.

Materials and Methods

Samples

Three commercial bakery products (coffee cookies, toasted bread, and muffins) were evaluated. They were all purchased in a local supermarket. Samples were cut into pieces (2 × 2 × 1 cm). Products were selected because they all had similar characteristics; wheat flour was the main component, air incorporation into dough by using either a rising agent or whipping (coffee cookies and muffins) or by fermentation (bread) and oven cooking. Yet they also had different characteristics linked with their composition (fat, sugar or water content; Table 1) and processing, both of which generated their final physical characteristics; glass state related to fracture point (toasted bread and cookies) or apparent density (Table 1).

Table 1 Approximate food composition obtained from the commercial label

	Muffins	Toasted bread	Coffee cookies
Wheat flour (%)	23	80	30
Fat (%)	23	1.5	26
Sugars (%)	25	4.9	25
*Water (%)	12	2	2.8
**Apparent density (kg/m^3)	0.92	0.48	1.68

* Obtained by dehydration in an oven until constant weight

** Obtained from measuring samples’ weight and volume

Participants

The study was carried out with eight healthy participants (four men and four women aged 24–49 years), with normal occlusion and a continuous dental arch according to the information they reported. All the participants were informed about the study objectives, the products to be eaten, the methodology of proof, and their anonymity.

Texture Measurements

The texture of each sample was determined by running the Kramer shear test and the texture profile analysis (TPA), both in a TA.XT2 Texture Analyzer (Stable Micro Systems, Surrey, UK) with a 25-kg load cell. Ten samples of each product, all of the same dimensions, were prepared and analyzed. For the Kramer shear test, a cell HDP/MK05 with a 5-bladed head was used at the deformation rate of 2 mm/s. The evaluated parameters were maximum force (Fmax (N)) and work (N·mm). For the TPA, a 35-mm diameter probe was employed. Test speed was set at 1.7 m/s to compress samples to 50% of their previous height. The time between compressions was 5 s. For coffee cookies and toasted bread, only the first compression was taken into account because they reached their fracture point and the evaluated parameter was fracture force. For muffins, two compressions were used. The studied parameters were hardness, springiness, cohesiveness, gumminess, and resilience (Rahman et al., 2021).

Chewing and Swallowing Tests

Chewing and swallowing tests were carried out for 5 days over 2 weeks. The participants ate three products daily, and rinsed their mouths before and after each one. The order in which products were provided differed every day and also per panelist. The order of panelists was also different on each sampling day.

The procedure to capture face movement during the test was the following:

Six face points (P1: temporomandibular joint, P2: jaw angle, P4: mental protuberance, P3: the midpoint between P2 and P4; P5: hyoid bone; P6: middle of the forehead) (Fig. 1A) were firstly cleaned with facial alcohol solution in which a sticker reflective marker was placed (Fig. 1A). P6 was used to record translational and rotational head movements. Stickers were placed by palpation. Once the participants were seated and height was adjusted, their heads were immobilized by a headband. The product was placed on their hand. After turning the light off, they put it in their mouths (on the top of their tongue), closed their mouths, and recording started by means of an acoustic signal produced by them. Once they had swallowed the product, recording was stopped by the acoustic signal.

The capture system was a digital Logitech C920 camera (CMOS sensor, resolution of 2304 × 1535). Images were captured at 30 frames per second in the RGB (red, green, and blue) format and were saved as mp4 (1980 × 1080). The camera was placed 30 cm from faces at an angle of 45°.

Image Processing and Data Extraction

The obtained movies were cut into frames and image stacks were created (Fig. 1B[a]). Employing the software developed by the group, coordinates X and Y of the track of each facial point during chewing and swallowing were obtained (Fig. 1B[b]). To process them, first the values of X and Y from P1 to P5 were amended with those from P6 to minimize any translational and rotational head movements that could have occurred. Then the two data processes were employed. In the first one, eight direct descriptors used by other authors were obtained from the X and Y coordinates (Table 2 and Fig. 1C.1) (Iguchi et al., 2015; Le Révérend et al., 2016; Remijn et al., 2016; Rivera et al., 2020; Wilson et al., 2016) with a software developed by the group. For that purpose, start of chewing was defined as the first jaw opening to occur and was evaluated in P4. End of swallowing was evaluated in P5, when the thyroid cartilage went back to the initial point (after swallowing). Chewing cycles were evaluated in P4 with the number of down and up jaw movements (points 2 in Fig. 1C.1). The swallowing process was detected in P5 by looking for the highest value and the points at both sides with the median value (area with the blue lines in Fig. 1C.1).

During the second data process, indirect descriptors were obtained by employing another software developed by the group. This process can help to minimize the effect of panelist attributes to enhance the effect of food on common facial movements. For each X and Y tracking value obtained at all the five facial points (Fig. 1B), the maximum and the minimum values of each oscillation during chewing and swallowing were obtained, and the number of frames between both (X-axis distance = □F) and pixels (Y-axis distance = □P) was extracted (Fig. 1C.2). Then as the time for each chewing and swallowing test differed, the □F and □P values were normalized with the total frames of the test. With normalization, the time factor was minimized to once again enhance the effect of food on facial movements. Two histograms were developed. In the first one, the □F values were clustered into 10 intervals, which were obtained by segmenting the maximum □F value into 10 equal units. The histogram was obtained with the number of □F within each interval. The procedure was similar for the second histogram, but the maximum □P was divided into 40 equal segments. The second histogram was obtained with the number of □P in each one (Fig. 1C.2). Histograms were generated by employing information not only from the entire eating time (TT), but also for the four quartiles of time into which each eating test

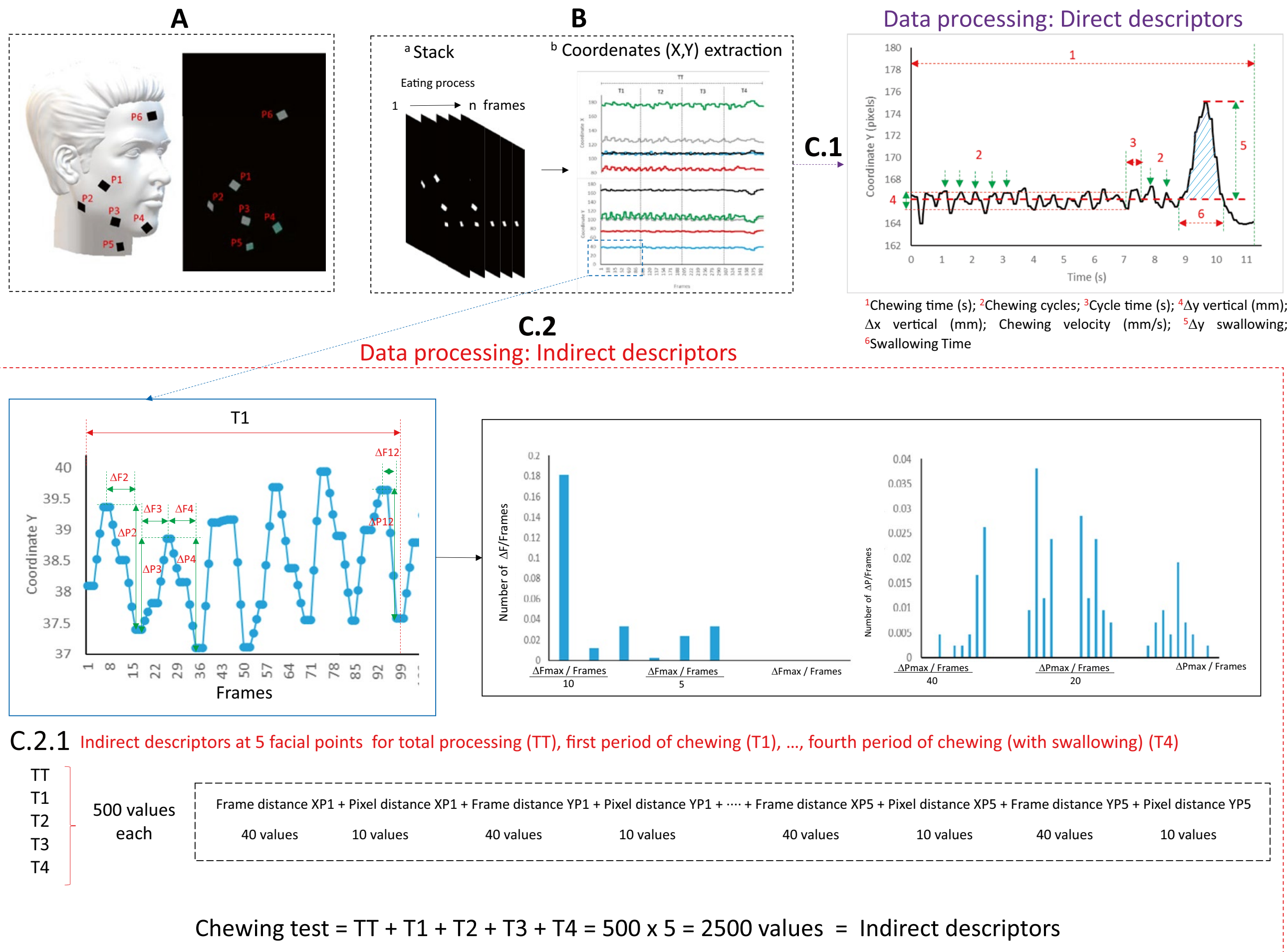

Fig. 1 Imaging capture, processing, and data extraction. **A** Facial point location. **B** Tracking of each facial point during chewing (a) to obtain the X and Y coordinates (b) and their processing (c). (C.1) Scheme of the variables (values) cataloged as indirect descriptors

was divided (T1, T2, T3, T4) (Fig. 1Bb). This was done to evaluate different chewing and swallowing periods. Masticatory performance is adapted not only cycle by cycle, but also throughout the bolus formation process (Iguchi et al., 2015). For each test, information was obtained by the summation of TT + T1 + T2 + T3 + T4 on each X and Y of the five facial points. Thus, by means of this process, the chewing and swallowing tests were described by 2500 values (Fig. 1C.2.1).

Table 2 Direct descriptors obtained from the X and Y coordinates of the five facial points during chewing and swallowing. The numbers on descriptors are represented in Fig. 1C.1

Descriptor	Description
[1]Chewing time (s)	Interval time between start of chewing and end of swallowing
[2]Chewing cycles	Number of down and up jaw movements
[3]Cycle time (s)	Mean time of one cycle
[4]□y vertical (mm)	Mean of the displacement on the Y-axis during the first 2/3 of chewing at P4
□x horizontal (mm)	Mean of the displacement on the X-axis during the first 2/3 of chewing at P4
Chewing velocity (mm/s)	Mean time for □Y vertical
[5]□y swallowing	Mean of the displacement on the Y-axis during swallowing. Distance between the median and the highest value in P5 (Fig. 1.C1)
[6]Swallowing time	Time needed for swallowing. Distance in pixels (transformed into seconds) between the median values on both sides of the highest value in P5 (Fig. 1C.1)

Statistical Analysis

The Kramer and TPA texture parameters (fracture force, work, hardness, springiness, cohesiveness, gumminess, chewiness, and resilience) of the three products were evaluated by an ANOVA. In those cases with a significant effect ($p < 0.05$), the average was compared by Fisher's least significant difference (LSD). To evaluate how the texture parameters described each product in relation to the others and their capacity to classify the three products, PCA and PLS-DA analyses with the pretreatment "GLSW filter" were applied.

The results of the direct descriptors obtained by the image processing of the chewing/swallowing tests were statistically analyzed by a multifactorial ANOVA, where panelists and products were the two factors. In those cases in which the product was significant ($p < 0.05$), a one-way ANOVA was run and the average was compared by Fisher's LSD. As with the texture parameters, PCA and PLS-DA with a GLSW filter were also applied to evaluate the capacity of direct descriptors to develop a model capable of describing and classifying the three products.

For indirect descriptors, PCA and PLS-DA analyses with a GLSW filter were also applied. To study the different periods of chewing and swallowing processes, six PLS-DA were applied: one employed all the generated data (TT + T1 + T2 + T3 + T4); the remaining five were one per quartile from T1 to T4, and the last one for the total eating time (TT).

To assess whether the imaging data were related to textural food characteristics, a partial least squares regression (PLS) analysis was performed. For the three products, the relation was evaluated by Kramer Fmax and work, and hardness and work from the first compression of the TPA. The relation with fracture point was evaluated only for coffee cookies and toasted bread.

The PLS-DA results were expressed as the sensitivity and specificity of the cross-validation (CV) results. The method followed for the CV process was "Venetian blinds" and employed three data splits. For the PLS, "Venetian blinds" was also used and accuracy was expressed as root mean square error (RMSE CV) and the coefficient of determination as R^2 CV.

These procedures were run with the PLS Toolbox, 6.3 (Eigenvector Research Inc., Wenatchee, Washington, USA), a toolbox extension in the Matlab 7.6 computational environment (The Mathworks, Natick, Massachusetts, USA).

Results and Discussion

Texture Characterization

Table 3 shows the results of the texture parameters for the three tested products. The results evidenced the large difference for muffins with the lowest values for the Kramer parameters (Fmax and work) and the compression test (hardness and work), and with no fracture point. The complex mixture of interacting ingredients for muffins (basically sugar and variable levels of fat, flour, eggs, and baking powder) generated the typical porous structure and a large volume to contribute to their soft, spongy, and tender crumb texture with a certain degree of resistance to crumbling (cohesiveness) (Öztürk & Mutlu, 2018). According to the authors (Hadnadev et al., 2018), two factors are essential for muffins' characteristics and to distinguish them from coffee cookies and toasted bread. The high water content (Table 1), and the two generated networks responsible for cell wall to gas retain: (1) a continuous egg protein gel network, formed during baking; (2) starch gel, formed while cooled (not evaluated in the

Table 3 Means and standard deviations for the texture analysis (Kramer test and TPA) and the PLS scores of the models developed to observe the relation between imaging data at T4 and the texture parameters

	Means SD			PLS scores			
	Muffins	Coffee cookies	Toast bread	RMSE C	RMSE CV	R^2 C	R^2 CV
[1]Fmax (*N*)	7.41 ± 2.04c	127.94 ± 2.36a	104.06 ± 2.58b	5.578	19.05	0.99	0.87
[1]Work (*N*·mm)	71.1 ± 17.67c	945.19 ± 20.41a	486.32 ± 18.89b	38.036	111.278	0.99	0.9
[2]Hardness (*N*)	11.03 ± 4.84c	255.28 ± 5.59b	281.47 ± 5.59a	13.761	46.17	0.98	0.87
[2]Fracture (*N*)	—	255.28 ± 5.59b	281.47 ± 5.59a	0.297	2.974	0.99	0.9
[2]Work	35.56 ± 17.20c	1071.72 ± 21.76a	733.94 ± 19.86b	50.74	141.782	0.98	0.89
[3]Springiness	0.699 ± 0.031	—	—	—	—	—	—
[3]Cohesiveness	0.449 ± 0.02	—	—	—	—	—	—
[3]Gumminess	5.08 ± 0.87	—	—	—	—	—	—
[3]Chewiness	3.55 ± 0.65	—	—	—	—	—	—
[3]Resilience	0.137 ± 0.007	—	—	—	—	—	—

A parameter with superscript 1: obtained from the Kramer test; superscript 2: obtained from the first compression of the TPA test; superscript 3: from all the TPA tests

A different letter in the same row means differences ($p < 0.05$)

study). Unlike bread dough, the abundant amount of water in muffins batter allows all the starch granules to be completely gelatinized to, thus, form a structure that entraps air bubbles (Hadnadev et al., 2018).

The differences between coffee cookies and toasted bread were smaller and dependent on the applied testing method. In the Kramer test, both maximum force and work were greater for coffee cookies, perhaps because of its higher apparent density. Behavior was not the same in the compression test because Fmax, which reached the fracture point, was higher for toasted bread, while work was higher for coffee cookies. The higher wheat flour content, which implies a bigger starch network, and the lower sugar content, which breaks down the network, confer the toasted bread dough greater binding. Instead, the higher apparent density of coffee cookies could be the reason for the obtained higher work value.

The PCA was done to evaluate how the three products were described when compared to one another based on the texture parameters and by taking a value of 0 for those not measured (fracture force for muffins; springiness, cohesiveness, gumminess, chewiness, and resilience for toasted bread and coffee cookies) (Fig. 2A). PC1 with 94.26% of total variance discriminated muffins (positive X-axis) from both coffee cookies and toasted bread (negative X-axis). PC2 with 4.14% of total variance discriminated coffee cookies (positive Y-axis) from toasted bread (negative Y-axis).

Image Analysis

During oral food processing (chewing and swallowing), lots of facial movements take place. By way of example, only during swallowing does the mandibular anchorage to the cranium occur as a primary physiologic event. It allows the action of the tongue and the suprahyoid muscles on the hyoid bone in all the swallowing phases. The hyoid bone moves upward in the first swallowing phase; at the same time, the jaw also moves upward to reach occlusal contact. At the end of deglutition, the hyoid bone moves downward and the jaw, by leaving occlusal contact, also moves downward to occupy its rest position (Monaco et al., 2008). During tests, some facial movements took place at the five evaluated facial points, but they did not occur with the same intensity and showed differences for the three products and panelists (Ketel et al., 2019; Woda et al., 2006). By way of example, Fig. 3 depicts the tracking coordinates (X and Y) at P1. It was initially possible to observe chewing cycles (one marked by a gray band), the first maximum jaw aperture that could express the first bite (blue dashed line with number 1), the swallowing point (red dashed line with number 3), start of the chewing process and end of swallowing (green number 4 and 5, respectively), and how the chewing process was not constant. From the X and Y coordinates of the tracking of the five facial points, two different data processes were followed to describe the products.

Direct Descriptors

Having obtained the direct descriptors, and according to that described in Table 2, a multifactorial analysis was applied. Its results showed a statistical effect ($p < 0.05$) for the panelist-product factors interaction, except for chewing time, cycle time, and swallowing time (Table 4). The panelist factor was significant ($p < 0.05$) for all the descriptors, but □y swallowing was not for the product factor. According to these

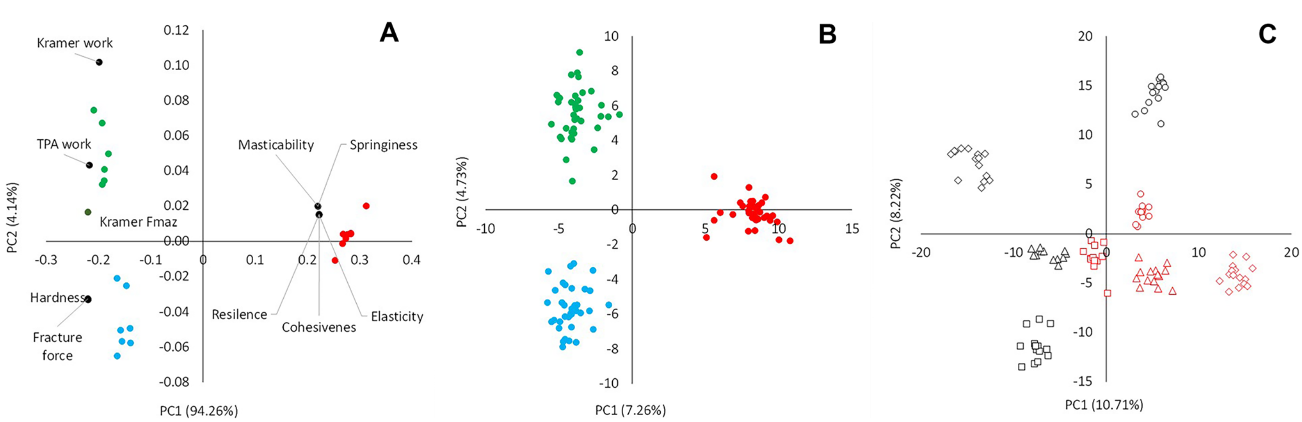

Fig. 2 Biplot for the first two main PCs of the PCA study applied to the texture parameters **A**. Plots of the first two PCs of the PCAs studies done with indirect descriptors, labeling samples according to products **B** or panelists **C**. Green dots, coffee cookies. Blue dots, toasted bread. Red dots, muffin. Black dots, variables (texture parameters). Empty red symbols, male panelists; empty black symbols, female panelists

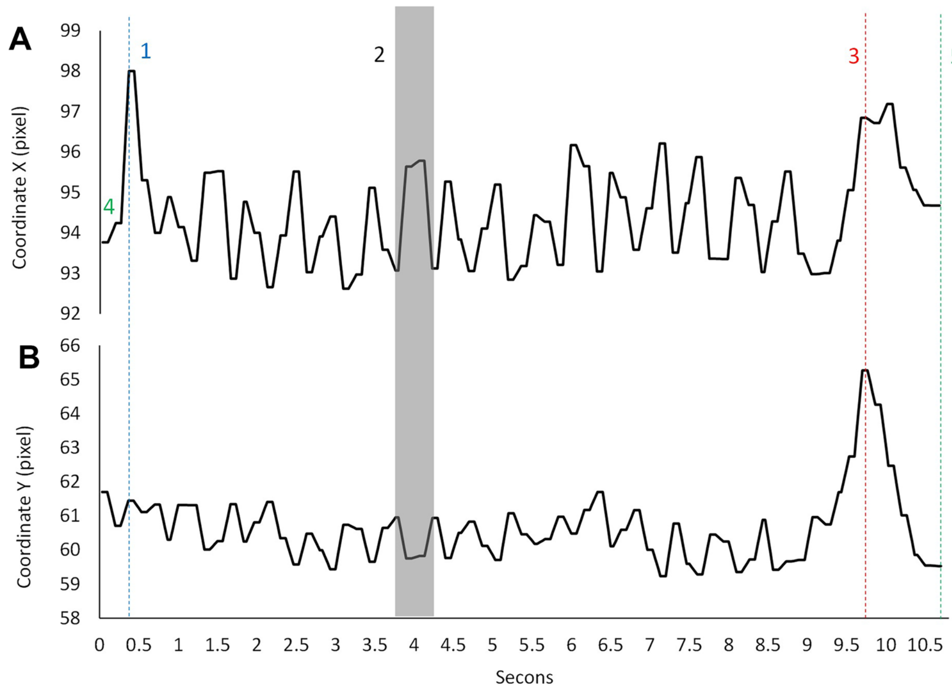

Fig. 3 The X **A** and Y **B** coordinates from the tracking at P1 during chewing processing

results, not all the panelists ate the three products in the same way, and panelist is an important factor to describe foods. Consumer characteristics, such as age, gender, and ethnicity, alter oral behavior (Ketel et al., 2019). Oral physiology plays an important role in the chewing process. Oral cavity size varies significantly from one person to another. A normal mouthful for adult males can take around 30.5 ± 10.1 g of water, but it takes approximately 25.2 ± 8.1 g of water for adult females. The number of teeth is also very important. Nevertheless, differences exist in the force applied by teeth even for people with all their teeth (Chen, 2009). Tooth cusp angle is also important and is related to the masticatory cycle near the maximal intercuspal, and malocclusion is often thought to perturb jaw movement and rhythm (Lassauzay et al., 2000). The role of the tongue is also significant. Its size, movement, and relation with oral cavity are other relevant factors, as is saliva. The tongue is essential for eating foods because of its interaction with them (Chen, 2009). In this way, gender had a statistical effect on all the descriptors, except for number of chewing cycles and chewing velocity. The one-way ANOVA applied for each descriptor evidenced a longer chewing time for women, with longer time for each, perhaps because of their greater X and Y displacements. Besides, they obtained lesser hyoid bone displacement and a longer swallowing time (Table 4).

Table 4 Significance of the direct descriptors for the multifactorial ANOVA. Means and standard deviations of the one-way ANOVA for product factor and gender

Direct descriptor	Factor significance			Differences between products			Differences between gender	
	Panelist (A)	Product (B)	AxB	Coffee cookies	Muffins	Toasted bread	W	M
Chewing time (s)	0	0	0.0536	24.73 ± 5.72a	16.87 ± 4.97b	20.18 ± 4.55c	22.21 ± 5.48a	19.55 ± 5.97b
Chewing cycles	0	0	0.047	38.82 ± 8.08a	26.24 ± 7.63b	32.34 ± 6.88c	32.36 ± 8.85a	32.58 ± 9.37a
Cycle time (s)	0	0.047	0.16	0.86 ± 0.10ab	0.88 ± 0.10b	0.83 ± 0.09a	0.93 ± 0.08a	0.80 ± 0.13b
△ y vertical (mm)	0	0	0	10.63 ± 2.86a	7.85 ± 2.80b	8.96 ± 2.80c	10.65 ± 3.58a	8.46 ± 2.29b
△ x horizontal (mm)	0	0	0.002	6.10 ± 2.29a	4.43 ± 1.87b	5.71 ± 2.54a	6.09 ± 2.07a	4.81 ± 2.40b
Chewing velocity (mm/s)	0	0	0.01	12.27 ± 2.74a	9.48 ± 3.48b	11.40 ± 3.11a	11.33 ± 3.49a	10.63 ± 2.95a
△ y swallowing	0	0.021	0.046	6.13 ± 2.39a	5.39 ± 2.84a	6.08 ± 2.75a	4.67 ± 1.59a	7.07 ± 2.98b
Swallowing time (s)	0.023	0.944	0.857	2.06 ± 0.94a	2.11 ± 0.85a	2.05 ± 0.71a	2.31 ± 0.88a	1.80 ± 0.67b

A different letter in the same row means differences ($p < 0.05$)

All the descriptors, except □y swallowing and swallowing time (s), showed significant differences ($p<0.05$) in the three products when the one-way ANOVA for factor product was run (Table 4). Differences in the three products were found for chewing time, chewing cycles, and □y vertical, with the highest values for coffee cookies and the lowest value for muffins. For descriptors □x horizontal and chewing velocity, values were the same for coffee cookies and toasted bread, but lower for muffins. Only cycle time had higher values for muffins. The lower hardness and density values can be associated with the shorter time needed to eat, the fewer chewing cycles for swallowing, and the shortest jaw course (□x and □y) (Slavicek, 2010). Hard and dry products required more chewing cycles and a longer time in the mouth until swallowing. It is necessary to reach sufficient breakdown and enough saliva needs to be added to form a coherent bolus that is safe for swallowing (Engelen et al., 2005). Increasing the hardness and elasticity of solid foods has been shown to increase chews per bite and decrease bite sizes (Bolhuis & Forde, 2020). High cohesiveness could slow down chewing velocity and, therefore, prolong the cycle time. Not only hardness, but also other parameters like cohesiveness, should be considered determinants of chewing behaviors, such as total chewing duration and number of chewing cycles before swallowing (Iguchi et al., 2015). As cohesiveness is the degree to which a material can be deformed before it breaks, it suggests that differences in cohesiveness have a critical effect not only on the whole masticatory sequence, but also on chewing performance per cycle (Iguchi et al., 2015).

Although there were significant differences because of product factor, as Fig. 4 depicts (with box-and-whisker plots), the chewing cycles, chewing time, chewing velocity, and □y vertical values were widely dispersed, even though all their means were higher for coffee cookies, then for toasted bread and finally for muffins. As previously mentioned, the weight of the panelist factor was considerable on chewing response and, therefore, on direct descriptors. This was why products did not cluster (data not shown) when all the data from direct descriptors were used together to describe products by comparing each one by a PCA. In the same way, the PLSDA model developed for classifying the three products gave sensitivity and specificity values below 70% (Fig. 5). The worse classification was for coffee cookies and toasted bread because the model was unable to discriminate between both.

Thus, using direct descriptors can help us to somewhat describe food texture (mainly hardness and cohesion), but a description is not enough to compare foods with similar characteristics.

Indirect Descriptors

Like direct descriptors, indirect descriptors were also used to evaluate products by the PCA. The spatial representation of the first two components of the PCA, done by labeling samples according to products, showed the same distribution of products as observed when texture parameters were employed (Fig. 2B and A, respectively). PC1 (7.26% of total variance) discriminated muffins (positive X-axis) from coffee cookies and toasted bread (negative X-axis), while PC2 (4.73% of total variance) discriminated the last two (coffee cookies with a positive Y-axis; toasted bread with a negative Y-axis). The textural characteristics of the eaten foods produced different movements at the five evaluated points, which were enough to discriminate among them and in the same way as employing the textural analysis values. When the PCA was done by labeling samples according to panelists, five components had maximum variance (36.95% of total variance). The spatial representation of the two first clustered panelists was in accordance with gender (Fig. 2C). It is known that there are gender differences in the spatio-temporal parameters of chewing movement path and rhythm (Shiga et al., 2012). Males have significantly larger bite sizes, shorter chewing cycle duration, and a faster eating rate than females. Males also use more chewing power than females (Park & Shin, 2015; Woda et al., 2006). Within the 2500 values (descriptors), obtained from transforming tracking facial point movements into histograms, data were obtained to describe chewing and swallowing processes as a fingerprint of products, and also panelists. The use of all the data obtained during

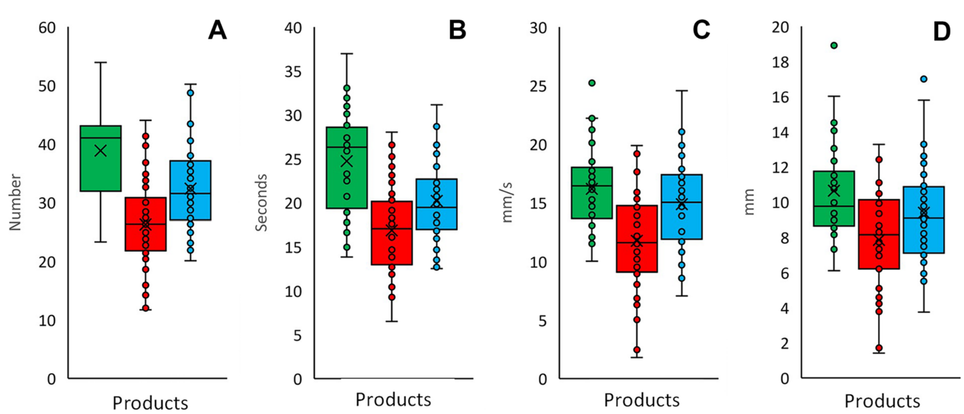

Fig. 4 Box-and-whisker plots for direct descriptors chewing cycles **A**, chewing time **B**, chewing velocity **C**, and Δy vertical **D**. Green, coffee cookies. Blue, toasted bread. Red, muffins

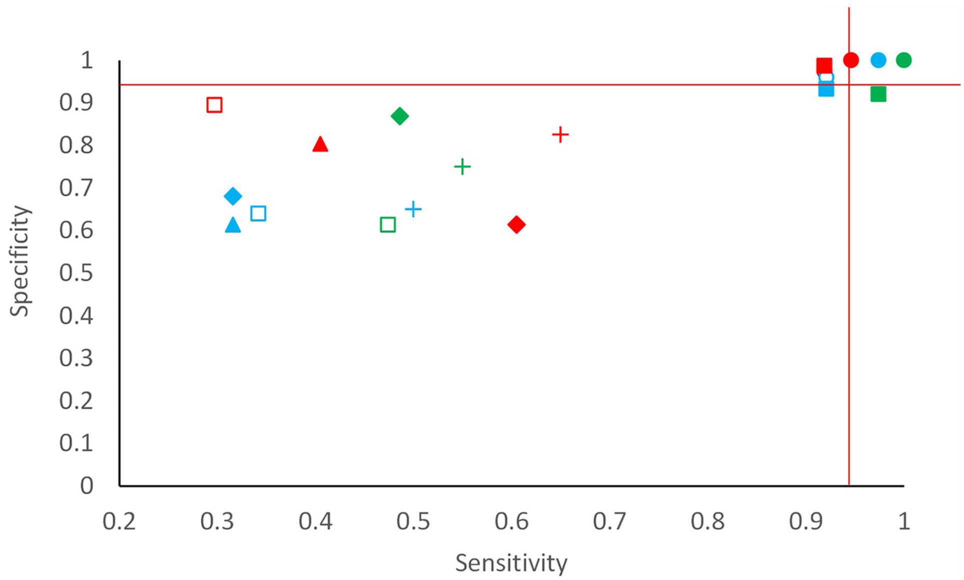

Fig. 5 Relation between the sensitivity and specificity for the PLSDA analysis. Green, coffee cookies. Blue, toasted bread. Red, muffins. Cross, data obtained from direct descriptors. Other symbols, data obtained from indirect descriptors. Filled squares, TT + T1 + T2 + T3 + T4. Empty squares, T1. Empty dots, TT. Filled dots, T4. Filled triangle, T2. Filled diamond, T3

the test, their transformation into histograms, and employing multivariant statistical tools increased the capacity of the sticker reflective markers and a camera for characterizing food product texture compared to others in a model (relation between Fig. 2A and B), but by taking into account both product and panelist effect (Fig. 2B and C, respectively).

The PCAs revealed that during chewing and swallowing processes, some movements were characteristic of the eaten food, and independently of panelist. At the same time, all the panelists made movements that characterized them. By way of example, Fig. 6 shows the histogram values of □P for the X and Y tracking at P1 during the last period of chewing and

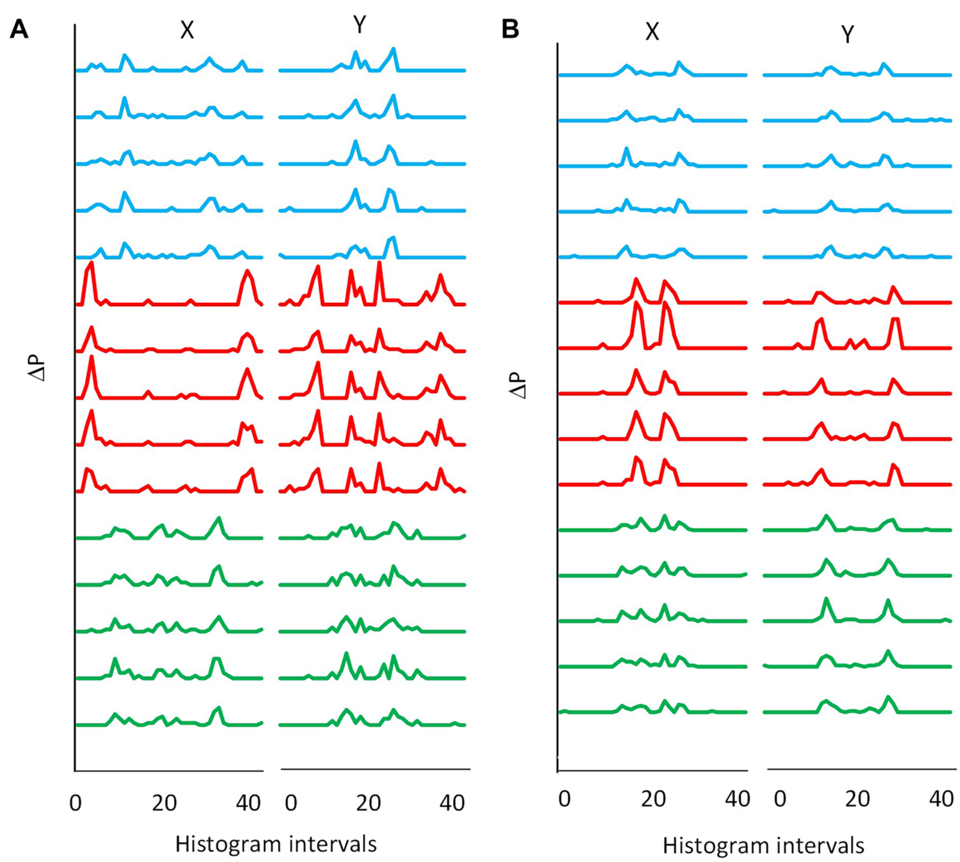

Fig. 6 Histogram values of ΔP for X and Y tracking at P1 during the last period of chewing and swallowing processes (T4) for two panelists: **A** and **B**. Y-axis (ΔP) is autoscaled for each series. Green, coffee cookies. Blue, toasted bread. Red, muffins

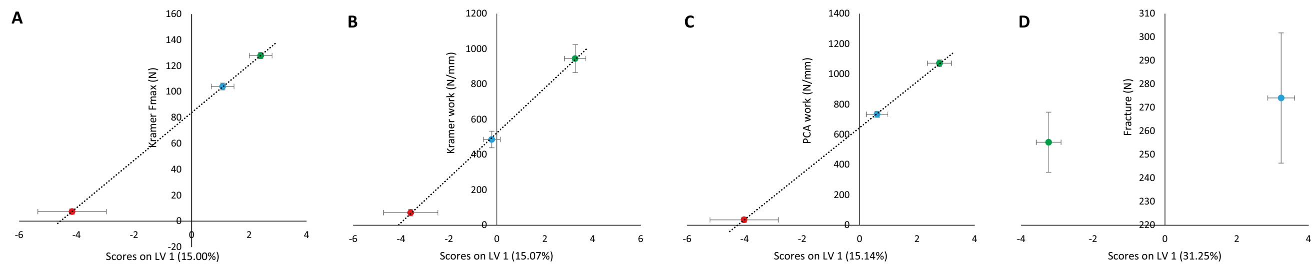

Fig. 7 Relation between the scores from the first latent variable from PLS and the texture parameters. **A** Kramer maximum force (N). **B** Kramer work (N·mm). **C** and **D** Work and fracture force (N), obtained from the first compression test of the TPA

swallowing processes (T4) for two panelists: A and B. For each one, the reproducibility of each product was high considering that tests were done for 5 days over 2 weeks. At the same time, and also for each one, chewing and swallowing processes were characteristic of the eaten product, but were different for each panelist. In 1972, according to the geniohyoid, anterior belly of digastric, mylohyoid, and genioglossus muscles movement, Hrycyshyn and Basmajian (1972) described how each individual has his/her own swallowing pattern, but people may swallow quite differently. More recently, Lassauzay et al. (2000) and Woda et al. (2006) remarked that there were no significant differences between the values of the masticatory parameters for a given individual when asked to chew the same food several times, but variation between individuals was wide.

Based on the good PCA results, six PLSDAs were developed: one employing all the data (TT + T1 + T2 + T3 + T4) and the remaining five from the total and at each quartile of the testing period. As Fig. 4 depicts, when histograms were obtained with information from the last quartile of chewing and swallowing processes (T4), the obtained result was the best, with sensitivity and specificity values over 95%. When histograms were done with the information from all the data (TT + T1 + T2 + T3 + T4) or from the total period (TT), the results were also good, but values were 90%. According to the results, it was during the last chewing and swallowing period when the main facial movement differences appeared because of the product factor. The degree of grinding and its interaction with saliva to form the bolus could be the reason. This final phase corresponds to food bolus preparation and no longer to particle size reduction (Le Révérend et al., 2016). It is necessary for a bolus to be prepared with a precise (predetermined) texture (or structure) before it can be swallowed. So particle size (mechanical food properties defined as the breakage function) and its interaction with saliva flow are important influential factors (Chen, 2009) that take place in this last stage (T4).

PLS was performed to assess whether the information from the imaging data at T4 was related to textural food characteristics (Table 3). Models were developed for the texture parameters obtained for the three products (Kramer Fmax and work, and hardness and work from the first compression of the TPA,) with only fracture force for coffee cookies and toasted bread. Although the cross-validation R^2 values went from 0.87 to 0.9 (Table 6), PLS was not applied to obtain prediction models, but to visualize the relation between the image data and the texture data. Figure 7 shows the relation between the scores from the first latent variable from PLS (LV1, containing the highest proportion of explained variance), used as dimensionally reduced imaging data, with the measured values of the texture parameters. As R^2 reported, some linear relations evidenced the strong influence of food characteristics on facial movements and how they were captured by technology and were recorded in indirect descriptors.

Thus, the reduction in all the information acquired from chewing and swallowing processes to direct descriptors could partially describe the three products, mainly because of their hardness and cohesiveness, but were not enough to discriminate among them. The panelist effect strongly influenced descriptors by reducing their discrimination capacity. Instead when all the information was transformed into histograms as indirect descriptors, it was possible to characterize products with similar textures by applying multivariate statistical tools. In this case, information generated a fingerprint of chewing and swallowing processes that, despite being dependent on the panelist (Fig. 2C), was independent enough to generate a classification model with high specificity and sensitivity values (Fig. 4) that describes foods (Fig. 2A compared to B) given their relation to texture (Table 3 and Fig. 7).

Conclusion

The study evaluated data from tracking facial movements during chewing and swallowing processes by employing skin surface markers as a fingerprint to characterize textural food product properties.

The use of direct descriptors, obtained after transforming tracking into descriptors, somewhat describes products' texture (mainly hardness), but the recorded dispersion hinders the classification of products with similar characteristics. The panelist factor strongly impacts descriptors by widening data dispersion, which makes their use for developing models difficult.

The use of indirect descriptors, after transforming all the information into histograms and applying multivariate statistical tools, allows classification models to be developed to describe products texturally and in the same way as using a texturometer, even when the panelist effect is present. Thus, for each panelist, the reproducibility of eating each product is high. At the same time, and also for each product, chewing and swallowing processes are characteristic of the eaten product, which differ for each panelist.

Thus, using skin surface markers for tracking facial feature movements comes over as an effective technique when all the obtained information is processed together. New studies are being carried out to improve data processing to examine in more depth both the description of foods when they are eaten at different times and how panelists go about this.

Acknowledgements Authors gratefully thank the Research and Development Support Programs (PAID-11-22) from the "Universitat Politècnica de València".

Author Contribution Raúl Grau: conceptualization, methodology, investigation, resources, writing—original draft, supervision. Samuel Verdú: investigation, visualization, writing—original draft. Alberto J. Pérez: investigation, visualization, writing—original draft. Sergio Hernández: investigation, visualization; José M. Barat: writing—review and editing. Pau Talens: methodology, writing—review and editing.

Funding Open Access funding provided thanks to the CRUE-CSIC agreement with Springer Nature. Authors received funding from Research and Development Support Programs (PAID-11–22) from the "Universitat Politècnica de València".

Data Availability The authors confirm their availability to provide their data.

Declarations

Competing Interests The authors declare no competing interests.

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