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# Mastication Evaluation With Unsupervised Learning: Using an Inertial Sensor-Based System

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**ABSTRACT** There is a direct relationship between the prevalence of musculoskeletal disorders of the temporomandibular joint and orofacial disorders. A well-elaborated analysis of the jaw movements provides relevant information for healthcare professionals to conclude their diagnosis. Different approaches have been explored to track jaw movements such that the mastication analysis is getting less subjective; however, all methods are still highly subjective, and the quality of the assessments depends much on the experience of the health professional. In this paper, an accurate and non-invasive method based on a commercial low-cost inertial sensor (MPU6050) to measure jaw movements is proposed. The jaw-movement feature values are compared to the obtained with clinical analysis, showing no statistically significant difference between both methods. Moreover, We propose to use unsupervised paradigm approaches to cluster mastication patterns of healthy subjects and simulated patients with facial trauma. Two techniques were used in this paper to instantiate the method: Kohonen's Self-Organizing Maps and K-Means Clustering. Both algorithms have excellent performances to process jaw-movements data, showing encouraging results and potential to bring a full assessment of the masticatory function. The proposed method can be applied in real-time providing relevant dynamic information for health-care professionals.

**INDEX TERMS** Jaw movements, mastication, inertial measurement unit, artificial intelligence, adaptive algorithms.

## I. INTRODUCTION

Chewing is primarily an unconscious semi-autonomic act, where the dynamic structures of the stomatognathic system move the mandible or jaw to bring the teeth into intermittent contact, occluding and opening periodically. The proper chewing pattern consists in bilateral alternating, with bilateral power-sharing, alternating work, and relaxation with rotation movements of the jaw, providing a complete activation of the muscles and an orofacial equilibrium [1].

A performance analysis of the masticatory function provides relevant information for health-care professionals to conclude their diagnosis and to plan the ideal treatment [2]–[5]. Information about jaw movements during mastication provides an objective basis for the diagnosis and monitoring of the therapeutic progress of the masticatory system [6].

Clinical methods used to evaluate characteristics and patterns of mastication movements are usually of subjective analysis, compromising its reproducibility, such that the quality assessment depends heavily on the experience, training, and practice of healthcare professionals [5]. Different approaches have been explored to track jaw movements using force transducers, electromyography, electromagnetic markers, and *Kinect* sensors. However, these techniques are usually expensive, limiting its use in small and medium-sized clinics [7]–[11].

Previous works have explored MicroElectroMechanical Systems (MEMS) to develop devices and methodologies to support physical exam in healthcare services [12]–[14]. Flavel *et al.* published a pioneer work in 2002 using MEMS accelerometers to measure vertical movements of the human mandible [7]. Lin *et al.* [6] have developed a MEMS and explored it for mastication analysis; the reported results, as they are presented, regarding frequency and total chewing time, are not much useful information on chewing disorders for a healthcare professional. Minami *et al.* [16], [17] proposed a new method based on the standard jerk-cost test [15] evaluating the smoothness of the jaw movement with a non-commercial piezoelectric accelerometer.

Artificial and Computational Intelligence are fields that develop systems able to learn specific tasks to solve a given problem from experimental data. Unsupervised learning algorithms can recognize patterns among subjects, grouping similar experiences without needing feedback [18]. Intelligent algorithms are able to find patterns in complex scenarios, usually very hard and sometimes even impossible to be identified by humans [19]; with the possibility of a friendly graphical representation of the data relationships.

In this work, two commercial low-cost MEMS sensors (MPU-6050$^{TM}$) are explored to measure jaw movements; Wavelet processing allows to obtain temporal and spatial features such as displacement, amplitude, time-cycle and chewing side preference. The method is a low-cost, accurate and non-invasive tool for the acquisition of mastication features. Obtained results are compared with a well-consolidated clinical test, revealing the competitiveness of the approach.

Furthermore, we propose to use an unsupervised paradigm approach to group mastication patterns of healthy subjects and simulated patients with facial trauma performing; two clustering techniques were employed in this paper to instantiate the method: Kohonen's Self-Organizing Maps (SOM) [20] and K-Means Clustering (K-Mean) [21]. The method shows potentiality to simplify the kinetic-functional diagnostic, aiming at helping healthcare professionals to optimize the rehabilitation.

## II. METHODS

### A. EXPERIMENTAL SETUP

The MPU6050 devices combine a 3-axis gyroscope, and a 3-axis accelerometer on the same silicon die together with an onboard Digital Motion Processor$^{TM}$, which processes complex 6-axis MotionFusion algorithms, measuring angle and acceleration values in the three orthogonal directions [22], [23]. Sensor artifacts or electrical noise in the acquired signal are removed implementing Kalman filters [24], [25].

As represented in Fig. 1, the sensor (MPU6050) signals were acquired by using an Arduino UNO platform and transmitted via Bluetooth to a computer, where the signals have been processed/represented with a graphical interface (C++ and Processing) and a sample rate of 100 samples per second.

Previous works have reported that head movements are inherent to the chewing process [26], such that measurement

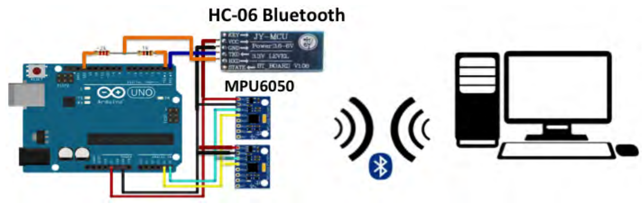


**FIGURE 1.** Experimental Intrumentation, the kinematic signals obtained by two MPU6050 inertial sensors were acquired with an Arduino UNO platform and transmitted via Bluetooth (HC-06) to a personal computer.

of jaw movements during the mastication is sensitive to redundant data information. A method to manage this artifact is to use a relative reference frame, only sensitive to head movements.

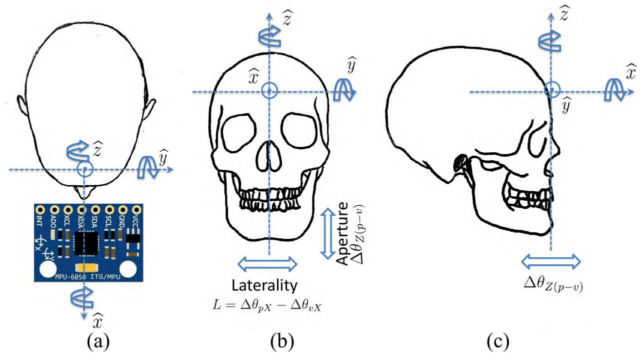


**FIGURE 2.** (a) Transverse plane and orientation/direction of the MPU6050 sensor (not at the same scale), (b) Frontal plane: Aperture and Laterality movements, (c) Sagittal plane.

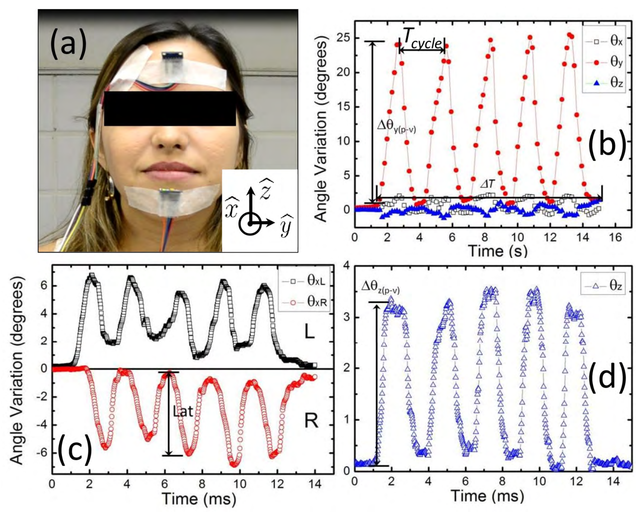


**FIGURE 3.** (a) Inertial sensors configuration, Simulated Jaw movement experiments: (b) Left, (c) Center and (d) Right. The data has been extrapolated to 100 points for better data visualization.

As represented in Figure 2, the forehead region is established as the origin of the reference frame (i.e. P(0,0,0)). Both MEMS sensors are oriented in the same spatial direction such that mandibular movements are described regarding the Cartesian axes given by the three orthogonal versors (i.e. $\hat{x}$, $\hat{y}$ and $\hat{z}$). As shown in Figure 3.a., one MEMS sensor is fixed on the jaw ($S_J$) and another (reference sensor) to the forehead ($S_R$) of the subject, measuring angle and acceleration values for the jaw movements concerning the reference sensor (e.g. $\theta_x = \theta_x(S_J) - \theta_x(S_R)$). Such configuration is non-invasive and does not interfere with the patient functions. For each individual sensor, the average value of the first ten acceleration and angle samples are defined as zero values, such that posterior measurements are relative values to zero.

### B. JAW-MOVEMENT FEATURES EXTRACTION

A trained subject has been oriented to simulate the three possible jaw movements for each orthogonal axis (i.e. opening, lateral and protrusion movements) repeating five times each movement to allow us verifying specific features represented in Figure 3.(b-d). All typical mastication signals are a composition of these orthogonal simulated movements.

The characteristics of jaw movements are extracted from the angle signal during each chewing cycle. A Gaussian Wavelet with a temporal size corresponding to nine samples is used to obtain temporal features such as the interval of each cycle, the total mastication time elapsed to complete the process, as well as, the peak and valley values of the angular signal. This kind of dynamic feature extraction [27] allows determining local variations during the mastication, where Fourier analysis or jerk-cost are not sensitive, providing a dynamic data processing in real-time.

As represented in Figure 3.b, the amplitude of the peak-valley value ($\Delta\theta_{Y(p-v)}$) is related to the total vertical aperture of the jaw. Moreover, the temporal features are the total ($\Delta_T$) and the elapsed time per Cycle (i.e. Time/Cycle, $T_{cycle}$) of the jaw movement. Considering the X-axis (i.e. $\Delta\theta_X$), the difference between peak and valley corresponds to the coefficient of laterality and is related to the chewing side preference, given by $L = \theta_R - \theta_L$. As shown in Figure 3.c., negative or positive values for the ratio of laterality mean mastication tendency to the right or left, respectively.

The values of peak-valley amplitude of the Z-angle (Fig. 3.d) represent part of the protrusion movement ($\Delta\theta_Z$). However, protrusion has not been analyzed in this study. Table 1 summarizes all the obtained jaw movement features.

**TABLE 1.** Jaw-movement features and related variables.

| Movement features | Variables |
|---|---|
| Total time jaw movement | $\Delta_T$ |
| Cycle Lapsed | $T_{cycle} = t_{p1} - t_{p2}$ |
| Vertical Amplitude | $\Delta\theta_{Y(p-v)}$ |
| Laterality | $L = \Delta\theta_{pX} - \Delta\theta_{vX}$ |

Similarly to the Jaw-Tracking report given by Electrognathography [28], it is possible to create a Sagittal and a Frontal scans of angle variations. As shown in Figures 4 (a) and (b), the patterns of the angular dependence $\theta_y$ vs. $\theta_x$ and $\theta_z$ vs. $\theta_x$ of the aforementioned simulated movements show opening and protrusion movements composing the sagittal plane, this kind of graphs should be more convenient for

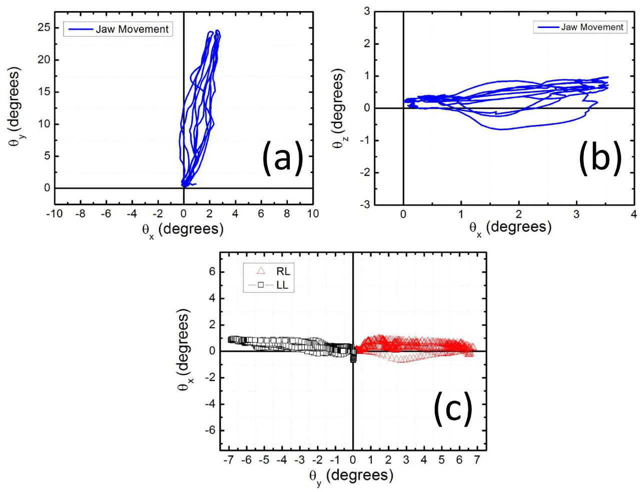


**FIGURE 4.** Patterns of the angular dependence of the same movements represented in Figures 2 (b-d). Sagittal scan: (a) $\theta_y$ vs. $\theta_x$, (b) $\theta_z$ vs. $\theta_x$; Frontal scan (c) $\theta_x$ vs. $\theta_y$.

a visual comparison between cycle movements. Moreover, the patterns of the angular dependence $\theta_x$ vs. $\theta_y$ distinguish lateral movements, both simulated movements (left and right) are easily identified in Figure 4.c.

### C. CLINICAL EXPERIMENTS-VALIDATION TEST

Ethics Committee in Research of the University of Pernambuco approved this research, CAAE - 37408714.3.0000.5192. The volunteers, conveniently aged 18-35 years, were selected in the local community. After signing the consent form, 60 participants, 30 Males and 30 Females, were included in the study after a previous examination, as long as they were healthy (i.e. have no diagnosed dysfunction).

The evaluation of the temporomandibular joints during the mastication was carried out based on the analysis of all the chewed food. The chewing movement data has been collected with the proposed method and a video camera, simultaneously and compared with the clinical assessment. We recorded the experiment with a camera (D3100 Nikon) to check the information acquired in the clinical evaluation that has been validated in the literature [29].

Although our system is not sensitive to head or body movements, the subjects have been oriented to sit on a wooden chair with their back against the backrest during the test. To perform the mastication function, we offered three different types of food in the following order: bread recently baked, apple and cookie (soft texture). The foods have been selected according to their different consistency, easy acceptance by volunteers and based on the literature [30], [31]. The subjects were oriented to masticate as many times as they usually do and then to swallow. We offered each food twice in a standardized order and amount. The guidance and time to place the sensors took approximately 4 minutes; the evaluation time, however, varied according to the number of cycles of each voluntary before ingesting the food.

The mastication data is processed with a statistical analysis to compare our proposed tool with the established clinical evaluation. In particular, the Kolmogorov-Smirnov test and the paired Student's t-test are implemented to verify whether the samples followed the normal distribution and whether the means of the two groups are statistically different from each other, respectively, what would imply a significant discrepancy between both methods. Moreover, McNemar test was used to compare nominal data (left or right). The statistical significance considered is $p<0.05$.

### *D. DATA PROCESSING - UNSUPERVISED LEARNING*

#### 1) SELF-ORGANIZING MAP - SOM

The SOM technique transforms a multi-dimensional space and its plotted points into a two-dimensional space, preserving the similarity between the data encoded into the distances between them [20].

During the training process, a given input data vector is presented to SOM, and the most similar output neuron (i.e., the closest) is select as the winner or best match unit (BMU). Neurons activated by a particular stimulus tend to trigger more strongly neurons that are in their immediate neighborhood than ones farther away. Due to this behavior, a kind of topological map is formed by neurons that are triggered whenever a particular type of stimulus or signal is perceived, which enables the clustering of similar patterns.

In Kohonen's original proposition of SOM, the Euclidean distance corresponds to the similarity criterion and the winner neuron is the one with the smallest distance [20]. Considering this process, the self-organization aims to minimize the distance, adjusting the BMU weights and its neighborhood toward the input vector using the following rule:

$$w_{ij}(t+1) = w_{ij}(t) + \alpha(t)h_{ci}(t)[x(t) - w_{ij}(t)], \tag{1}$$

where, $w_{ij}$ is the weight $j$ of neuron $i$, $\alpha(t)$ is the learning rate and $h_{ci}(t)$ is the neighborhood radius function centered on winner neuron $c$ with respect to neuron $i$. Typically, both learning rate and neighborhood radius are functions, which decrease with time, facilitating the system convergence.

#### 2) K-MEANS

K-Means clustering is a method of vector quantization for cluster analysis in data mining [21]. The K-Means technique is not able to present the data in a space with a smaller dimensionality than the number of features in the data. Another aspect of K-means is the mandatory request of class number prior to clustering operation.

Therefore, an algorithm to represent the data provided by K-means is proposed for a visualization in polar coordinates. The algorithm works following the next steps:

- Identification of the group's centroids extract by K-means;
- Identification of the regular group by the user (i.e. Therapist), based on the literature;
- Attribution of indices from 0 to $n$ and 0 to $m$ to samples of regular and injured patients, respectively. Where $n$ and $m$ are the number of samples to each group;
- The Point $P_j(x, y)$ of each index $i$ of group $j$ on a bi-dimensional space are defined by:

$$P_{ij}(x, y) = \left(d_{ij}\cos\left(i\frac{2\pi}{n}\right), d_{ij}\sin\left(i\frac{2\pi}{n}\right)\right) \tag{2}$$

  where $d_{ij}$ is the Euclidian sample distance $i$ of the group $j$ to the centroid of the regular group, measured on the hyper-dimensional space.

## III. RESULTS AND DISCUSSION

### *A. VALIDATION OF THE INERTIAL SENSOR-BASED SYSTEM TO TRACK JAW MOVEMENTS*

In the following subsections, the results of the comparison of the performed tests to compare clinical and the method proposed are presented (Tool). We have examined the total number of mastication cycles, total mastication time, and chewing side preference. For all analysis, a parametric statistic test has been utilized, considering that our sample follows a normal distribution.

#### 1) NUMBER OF MASTICATION CYCLES

As aforementioned, a paired t-test has been performed to verify possible differences between the number of mastication cycles obtained with both evaluation methods (the proposed technique and clinical examination) for the tested food.

**TABLE 2. Distribution of the total number of masticatory cycles.**

| FOOD | N | Min | Max | Mean | Median | Stdev | p-value |
|---|---|---|---|---|---|---|---|
| **FEMALE GROUP** | | | | | | | |
| **BREAD** | | | | | | | |
| Tool | 30 | 19 | 34 | 27.83 | 28.00 | 3.54 | **0.400** |
| Clinical | 30 | 20 | 35 | 28.46 | 23.82 | 3.54 | |
| **APPLE** | | | | | | | |
| Tool | 30 | 16 | 36 | 29.06 | 28.50 | 4.67 | **0.810** |
| Clinical | 30 | 13 | 36 | 29.00 | 28.50 | 4.57 | |
| **COOKIE** | | | | | | | |
| Tool | 30 | 21 | 36 | 28.90 | 28.50 | 3.68 | **0.870** |
| Clinical | 30 | 21 | 37 | 28.96 | 29.00 | 4.03 | |
| **MALE GROUP** | | | | | | | |
| **BREAD** | | | | | | | |
| Tool | 30 | 15 | 39 | 28.26 | 28.00 | 5.97 | **0.400** |
| Clinical | 30 | 15 | 40 | 29.26 | 30.00 | 6.36 | |
| **APPLE** | | | | | | | |
| Tool | 30 | 12 | 38 | 26.13 | 26.50 | 7.20 | **0.789** |
| Clinical | 30 | 12 | 37 | 26.30 | 27.00 | 6.76 | |
| **COOKIE** | | | | | | | |
| Tool | 30 | 11 | 38 | 26.13 | 25.50 | 6.04 | **0.483** |
| Clinical | 30 | 12 | 38 | 26.33 | 25.00 | 5.79 | |

The t-test results are summarized in Table 2 corresponding to the Female and Male groups, respectively. In addition to the t-test comparison, the tables contain detailed features, such as central tendency (i.e. mean and median) and statistical dispersion values (i.e. minimum, maximum and standard deviation).

Regarding the female group, the p-values are greater than the significance level, indicating an insignificant statistical difference between both applied methods. On the other hand, it is possible to see that the central tendency and the statistical dispersion values of such comparison are quite similar.

Similarly to the female group, the p-values obtained from the analysis of the male group, are also greater than the significance level. Therefore, the results confirm the acceptance of the null hypothesis that the samples are statistically equivalent.

### 2) TOTAL MASTICATION TIME

In the case of the mastication time to eat each food, the t-test demonstrates that there is no significant difference between the analyzed groups. The p-values obtained in the test are 0.968, 0.142 and 0.143 for Bread, Apple, and Cookie, respectively. Analogously in the case of the Male group, the p-values are 0.810, 0.935 and 0.851 for Bread, Apple, and Cookie, respectively.

**TABLE 3. Distribution of the masticatory total time.**

| FEMALE GROUP | | | | | | | |
|---|---|---|---|---|---|---|---|
| **FOOD** | **N** | **Min** | **Max** | **Mean** | **Median** | **Stdev** | **p-value** |
| **BREAD** | | | | | | | |
| Tool | 30 | 14.95 | 24.51 | 23.30 | 23.82 | 1.95 | **0.810** |
| Clinical | 30 | 13.33 | 24.00 | 23.70 | 23.18 | 1.67 | |
| **APPLE** | | | | | | | |
| Tool | 30 | 9.08 | 24.54 | 21.57 | 23.15 | 3.76 | **0.935** |
| Clinical | 30 | 10.00 | 23.38 | 22.07 | 22.77 | 4.08 | |
| **COOKIE** | | | | | | | |
| Tool | 30 | 13.42 | 24.51 | 23.07 | 24.03 | 2.37 | **0.851** |
| Clinical | 30 | 12.00 | 24.97 | 22.99 | 24.00 | 1.98 | |
| **MALE GROUP** | | | | | | | |
| **FOOD** | **N** | **Min** | **Max** | **Mean** | **Median** | **Stdev** | **p-value** |
| **BREAD** | | | | | | | |
| Tool | 30 | 21.16 | 24.38 | 23.40 | 23.63 | 0.80 | **0.968** |
| Clinical | 30 | 21.00 | 24.00 | 23.17 | 23.90 | 0.78 | |
| **APPLE** | | | | | | | |
| Tool | 30 | 7.00 | 24.20 | 20.60 | 23.23 | 5.76 | **0.142** |
| Clinical | 30 | 7.04 | 24.50 | 21.00 | 22.80 | 5.80 | |
| **COOKIE** | | | | | | | |
| Tool | 30 | 8.70 | 32.44 | 20.99 | 22.48 | 5.53 | **0.143** |
| Clinical | 30 | 9.00 | 33.00 | 21.18 | 22.00 | 5.47 | |

Table 3 shows the results of the mastication time to eat Bread, Apple, and Cookies for Male and Female groups.

The average times to eat the tested foods, measured by both techniques, are similar for the two groups of volunteers. The dispersion values indicated a higher data variability in the male group that the obtained for the female group.

### 3) CHEWING-SIDE PREFERENCE

As mentioned in the Jaw-movement feature extraction numeral, a negative or positive laterality coefficient indicates a right or left side preference, respectively, showing the tendency of a person to use a preferential side to masticate. Such behavior usually is related to a dental injury, a muscle imbalance or postural disorders.

**TABLE 4. Comparison of the chewing-side preference - Male group. McNemar's Test [32].**

| | | | Clinical Evaluation | | |
|---|---|---|---|---|---|
| **BREAD** | | | **Right** | **Left** | **Total** |
| Proposed Tool | **Right** | N | 11 | 8 | 19 |
| | | % PT | 57.9 | 42.1 | 100.0 |
| | | % CE | 73.3 | 53.3 | 63.3 |
| | | %Total | 36.7 | 26.7 | 63.3 |
| | **Left** | N | 4 | 7 | 11 |
| | | % PT | 36.4 | 63.6 | 100.0 |
| | | % CE | 26.7 | 46.7 | 36.7 |
| | | %Total | 13.3 | 23.3 | 36.7 |
| | **Total** | N | 15 | 15 | 30 |
| | | % PT | 50.0 | 50.0 | 100.0 |
| | | % CE | 50.0 | 50.0 | 100.0 |
| | | %Total | 100.0 | 100.0 | 100.0 |
| | | | **p-value = 0.388** | | |
| | | | **Clinical Evaluation** | | |
| **APPLE** | | | **Right** | **Left** | **Total** |
| Proposed Tool | **Right** | N | 13 | 7 | 20 |
| | | % PT | 65.0 | 35.0 | 100.0 |
| | | % CE | 81.3 | 50.0 | 66.7 |
| | | %Total | 43.3 | 23.3 | 66.7 |
| | **Left** | N | 3 | 7 | 10 |
| | | % PT | 30.0 | 70.0 | 100.0 |
| | | % CE | 18.8 | 50.0 | 33.3 |
| | | %Total | 10.0 | 23.3 | 33.3 |
| | **Total** | N | 16 | 14 | 30 |
| | | % PT | 53.3 | 46.7 | 100.0 |
| | | % CE | 100.0 | 100.0 | 100.0 |
| | | %Total | 53.3 | 46.7 | 100.0 |
| | | | **p-value = 0.388** | | |
| | | | **Clinical Evaluation** | | |
| **COOKIE** | | | **Right** | **Left** | **Total** |
| Proposed Tool | **Right** | N | 13 | 6 | 19 |
| | | % PT | 68.4 | 31.6 | 100.0 |
| | | % CE | 76.5 | 46.2 | 63.3 |
| | | %Total | 43.3 | 20.0 | 63.3 |
| | **Left** | N | 4 | 7 | 11 |
| | | % PT | 36.4 | 63.6 | 100.0 |
| | | % CE | 23.5 | 53.8 | 36.7 |
| | | %Total | 13.3 | 23.3 | 36.7 |
| | **Total** | N | 17 | 13 | 30 |
| | | % PT | 56.7 | 43.3 | 100.0 |
| | | % CE | 100.0 | 100.0 | 100.0 |
| | | %Total | 56.7 | 43.3 | 100.0 |
| | | | **p-value = 0.754** | | |

Table 4 contains the comparisons between the findings of lateral preference test for Bread, Apple, and Cookie in the male group respectively. The variable referring to the Chewing Side Preference (CSP) was analyzed using McNemar test since this is a nonparametric, nominal (right or left), and dependent variable. The percentage rates consist in a more understandable representation of the absolute values.

The p-values resulting from the male group analyzed with different foods, for the two different techniques were 0.388, 0.344 and 0.754. From these values, it is possible to see that there is no statistically significant difference for the CSP when compared to the values obtained from the technical and clinical analysis. In this case, the null hypothesis, which states that there is no significant difference between the technique and the clinical analysis, has been accepted in the three cases above as the p-value in each case was greater than 0.05.

**TABLE 5. Comparison of the chewing-side preference - Female group. McNemar's Test [32].**

| | | | Clinical Evaluation | | |
|---|---|---|---|---|---|
| **BREAD** | | | **Right** | **Left** | **Total** |
| Proposed Tool | **Right** | N | 6 | 10 | 16 |
| | | % PT | 37.5 | 62.5 | 100.0 |
| | | % CE | 54.5 | 52.6 | 53.3 |
| | | %Total | 20.0 | 33.3 | 53.3 |
| | **Left** | N | 5 | 9 | 14 |
| | | % PT | 35.7 | 64.3 | 100.0 |
| | | % CE | 45.5 | 47.4 | 46.7 |
| | | %Total | 16.7 | 30 | 46.7 |
| | **Total** | N | 11 | 19 | 30 |
| | | % PT | 36.7 | 63.3 | 100.0 |
| | | % CE | 100.0 | 100.0 | 100.0 |
| | | %Total | 36.7 | 63.3 | 100.0 |
| | | | **p-value = 0.302** | | |
| | | | **Clinical Evaluation** | | |
| **APPLE** | | | Right | Left | Total |
| Proposed Tool | **Right** | N | 18 | 2 | 20 |
| | | % PT | 40.0 | 60.0 | 100.0 |
| | | % CE | 18.2 | 75.0 | 33.3 |
| | | %Total | 13.3 | 20.0 | 33.3 |
| | **Left** | N | 4 | 6 | 10 |
| | | % PT | 40.0 | 60 | 100.0 |
| | | % CE | 18.2 | 75 | 33.3 |
| | | %Total | 13.3 | 20 | 33.3 |
| | **Total** | N | 22 | 8 | 30 |
| | | % PT | 73.3 | 26.7 | 100.0 |
| | | % CE | 100.0 | 100.0 | 100.0 |
| | | %Total | 73.3 | 26.7 | 100.0 |
| | | | **p-value = 0.289** | | |
| | | | **Clinical Evaluation** | | |
| **COOKIE** | | | Right | Left | Total |
| Proposed Tool | **Right** | N | 7 | 8 | 15 |
| | | % PT | 46.7 | 53.3 | 100.0 |
| | | % CE | 77.8 | 38.1 | 50.0 |
| | | %Total | 23.3 | 26.7 | 50.0 |
| | **Left** | N | 2 | 13 | 15 |
| | | % PT | 13.3 | 86.7 | 100.0 |
| | | % CE | 22.2 | 61.9 | 50.0 |
| | | %Total | 6.7 | 43.3 | 50.0 |
| | **Total** | N | 9 | 21 | 30.0 |
| | | % PT | 30.0 | 70.0 | 100.0 |
| | | % CE | 100.0 | 100.0 | 100.0 |
| | | %Total | 30 | 70.0 | 100.0 |
| | | | **p-value = 0.114** | | |

As the CSP for the male group, we performed McNemar test [32] analogously for females. Table 5 presents the results of the tests with bread, apple, and cookie. The p-values were 0.302, 0.289 and 0.114, respectively. Such result indicates no statistically significant difference between the techniques. Considering the number of episodes of laterality, the occurrence of the predominance to the right is superior to all food types, for the two groups (male and female) and both techniques.

In conclusion, the results show no statistically significant difference between the proposed analysis and traditional clinical evaluation. However, the validation, comparing it with the gold-standard method, is also necessary since both methods add a compatible bias related to their use and to the interference in the movement pattern. Such result indicates that our system could provide objective information regarding such evaluation, without adding necessarily any extra bias.

### *B. MASTICATION EVALUATION BASED ON UNSUPERVISED LEARNING*

For the mastication evaluation analysis, the experiments compare acceleration mastication values of healthy subjects and simulated subjects with Jaw pathologies. In particular, the simulation corresponds to patients with facial trauma performing masticatory movements.

Different configurations have been explored to gauge the SOM's and K-means' performances. Initially, Normal and Dysfunctional jaw mastication movements have been clustered using SOM with various iterations. Posteriorly, exploring the most efficient number of iterations, it is possible to compare the behavior for different foods within each group (Intra-Group). This experiment has been performed with both algorithms.

The dynamic behavior of masticatory movements has been analyzed with the following SOM settings: Neurons grid dimension: $20 \times 20$, $30 \times 30$, and $50 \times 50$; Convergence rate: 1.0 and 2.0; Learning rate: 0.1.

#### 1) SOM-NUMBER OF ITERATIONS

Normal and Disfunctional jaw mastication movements have been clustered using SOM with various iterations. Figure 5 shows the results using SOM for the Female Group, chewing Bread (a-c), Apple (d-f), and Cookie (g-i). Exploring 500 (a, d, and g), 1000 (b, e, and h) and 2000 (c, f, and i) iterations.

As shown in Figure 5, it is possible to notice a clear separation between the Normal and Non-normal groups. Such performance represents a high efficiency of SOM to cluster subjects according to masticatory features. Therefore, for the following subsections, SOM with 500 interactions has been used as default setting.

Figure 6 shows the Male (a, b, c) and Female (d, e, f) individuals, normal and non-normal, chewing bread (a, d), apple (b, e) and cookie (c, f) clustered by a SOM algorithm with 500 iterations. It can be clearly noticed that the approach is able to detect the difference among normal and non-normal subjects for both genders.

#### 2) K-MEANS - POLAR REPRESENTATION

For the K-Means experiment, two clusters and 500 interactions have been selected.

The polar-based 2-dimensional mapping of the K-Means clustering algorithm for both gender groups is represented in Figure 7. Individuals with normal mastication (filled points) are inside the circular area (filled circle) for all cases, while the non-normal ones (simulated pathologies) are outside the circle (non-filled circles).

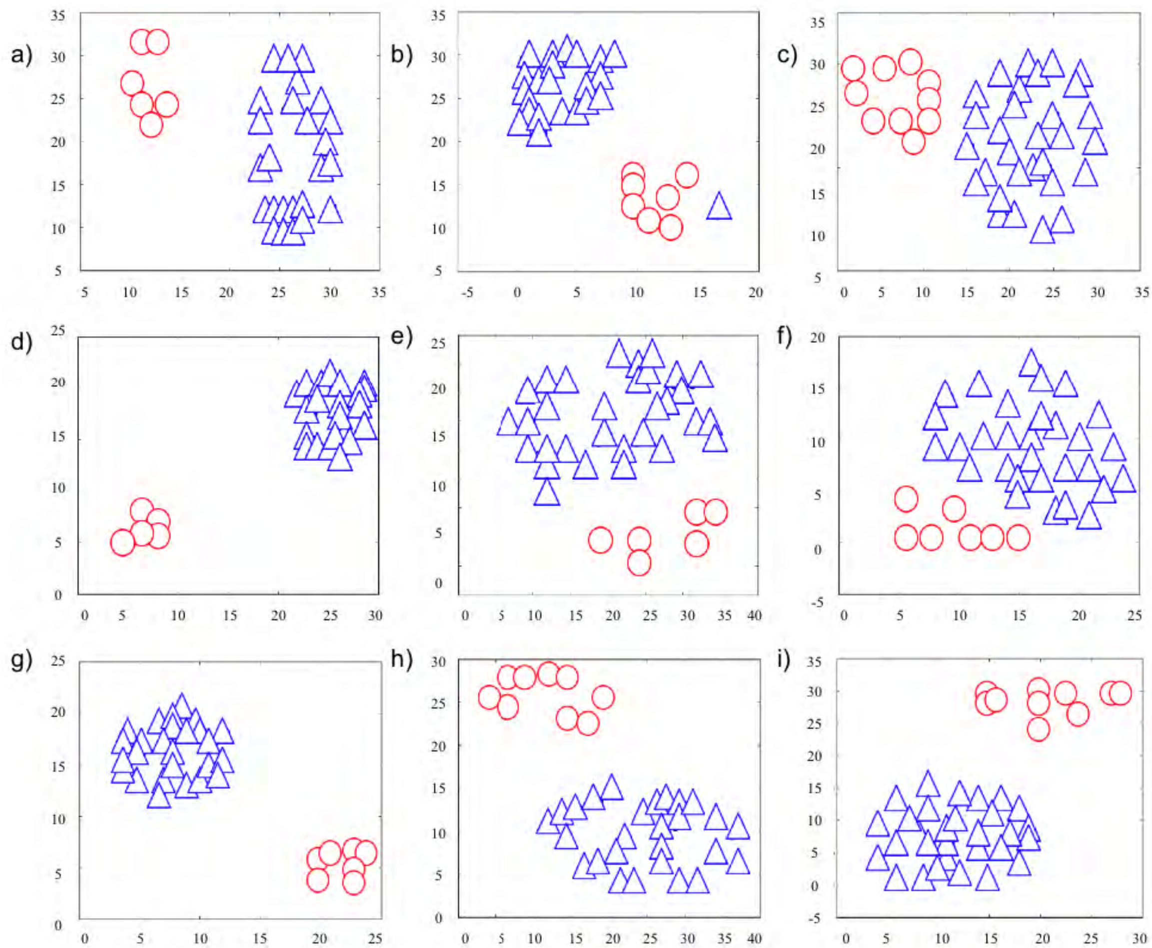


**FIGURE 5.** SOM clusters - Bread (a-c), Apple (d-f), and Cookie (g-i) - Female - Normal (△) x Disfunction (○) - Iterations: 500, 1000, and 2000.

On the other hand, comparing both gender groups, it is possible to see that the normality area of the Female group is smaller than the Male group one. Such difference corroborates the comparison results described previously in the Validation test numeral, where the samples of the Female group showed less variation than Male patterns. Therefore, considering the previously reported standard deviation values, a smaller normality area would be expected.

Trials with Bread (for both gender groups) show the smallest normality area, indicating an attractive option for the evaluation. For instance, considering that such region is more restrict, it may correspond to a challenging goal and, possibly, a more efficient rehabilitation goal.

The mentioned results show that both SOM and K-Means approaches can visually differentiate normal from non-normal mastication patterns for different subjects. However, both methods have advantages and drawbacks.

The SOM method presents multi-dimensional individuals in a 2-dimensional space, preserving its differences and similarities through their distances. On the other hand, the polar-based 2-dimensional visualization K-Means does not gauge the differences between individuals (exploring the gap between them), instead of this, it represents the distance between each mastication and the centroid of a regular chewing pattern, which is the center of the normality region.

In the case of K-Means, it is much more intuitive to evaluate how problematic is the mastication of a given subject and, consequently, it is possible to track the evolution during a therapy process. For instance, as can be seen in Figure 7.c there are individuals with different non-normal situations, showing several levels of non-normality. This effect may be explored to track a patient evolution achieved during its rehabilitation, such that on the occasion that the distance from the normality area was reduced, the therapy has been successfully applied.

Unlike the K-Means method, it is not possible to track evolutions of an individual during therapy, as represented in Figure 6.c.; SOM method shows only the separation between the normal and non-normal mastication patterns. According to the performed tests, we noticed that both SOM and K-means were able to group the different subjects even

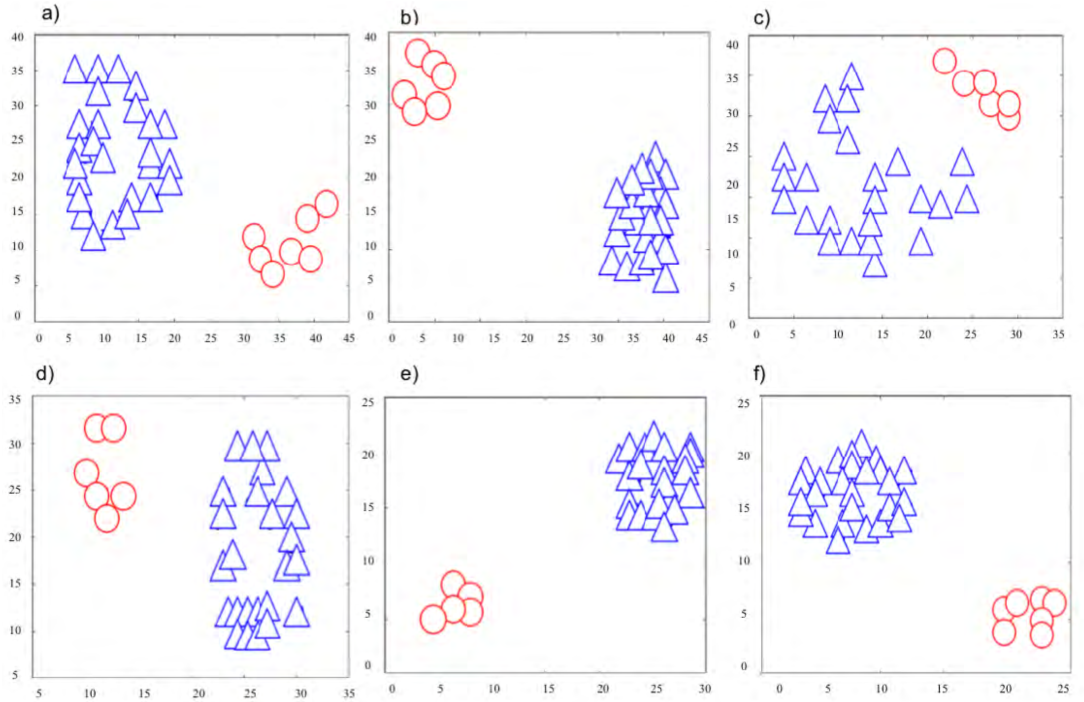


**FIGURE 6.** **SOM clusters with bread, apple, and cookie at the same time - Male (a,b,c)/Female (d,e,f) - Iterations: 500, 1000, and 2000.**

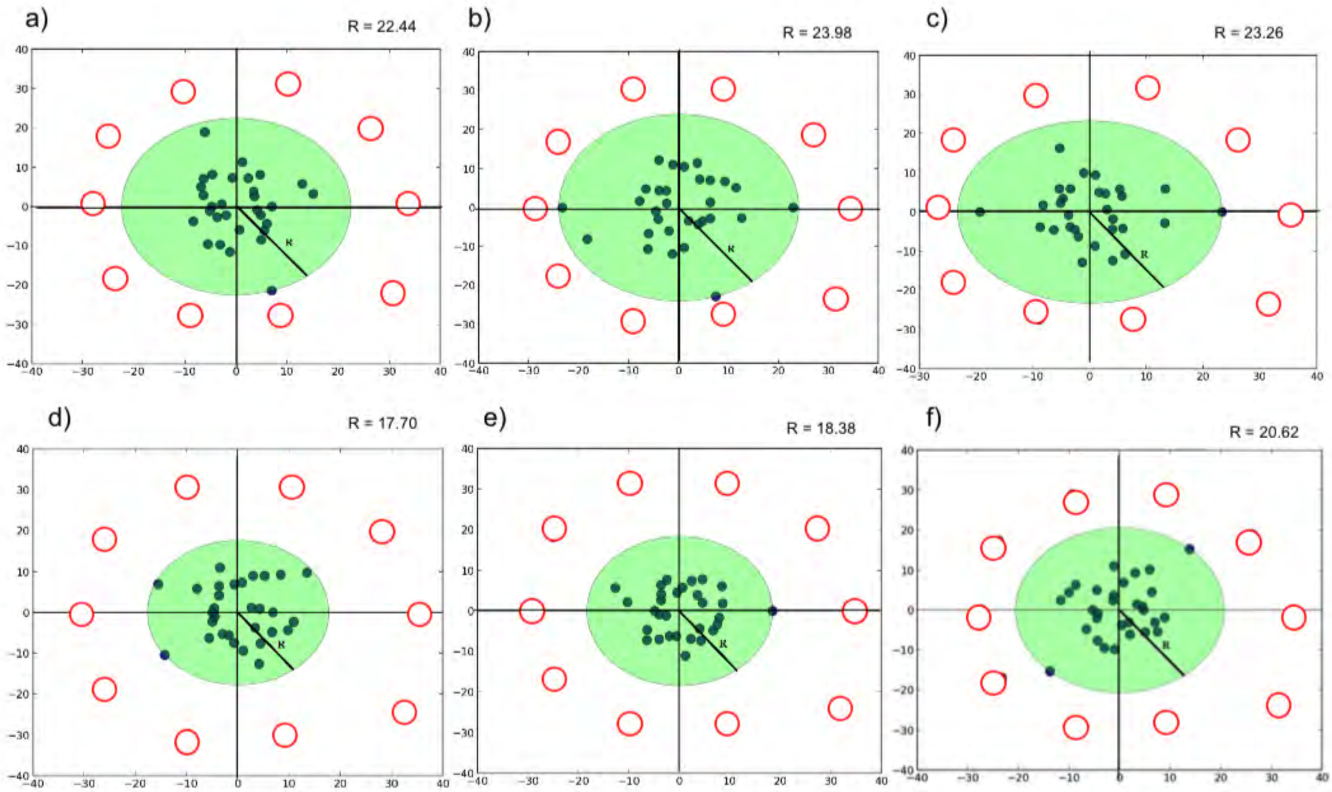


**FIGURE 7.** **K-Means clusters - Bread/Apple/Cookie - Male (a-c) x Female (d-f) - Normal x Disfunction.**

with a reduced number of iterations and a robust grid of neurons, elapsed time: 58.25 $\pm$ 2.16 and 55.38 $\pm$ 3.25 seconds, respectively. By increasing the number of iterations and neurons, the outcomes persisted, not justifying, thus, the inherent rise of the data processing time and computational cost.

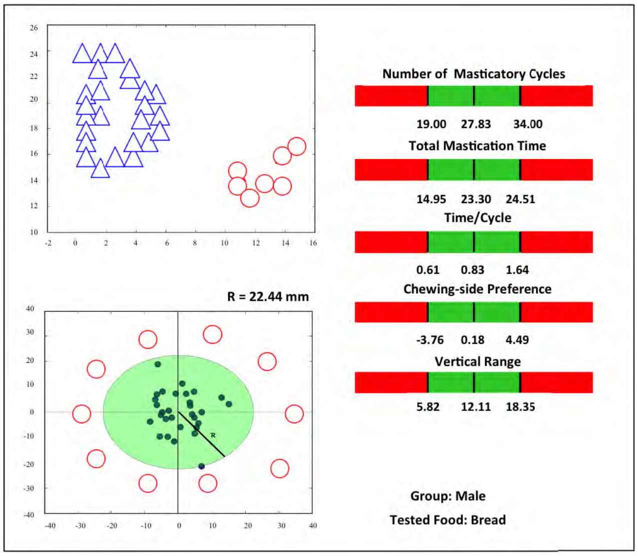


**FIGURE 8.** Assessment report.

### C. MASTICATION EVALUATION ASSESSMENT REPORT

Summarizing the mastication analysis method of this work, we propose an assessment report represented in Figure 8. The synthesized and intuitive description may be relevant to diagnose several dysfunctions. The put-forward report style brings an overview of the acquired data, including the results of SOM and K-means clustering, as well as, the Jaw-Movement features (*i.e.* Number of Masticatory Cycles, Total Mastication Time, Time/Cycle, Chewing-side Preference and Vertical Range).

Therapist and Patient may eventually notice an unbalanced pattern during the evaluation for each kinematic feature, comparing its results with the previously obtained by subjects with normal mastication. The use of such information as a feedback during the rehabilitation is arguably very useful. Therefore, in case a patient's data are within the green region of a specific kinematic feature, it means that it belongs to the normality group for this feature. Moreover, the closer is the patient's result to the center of the green area, the healthier is his Jaw mastication features.

On the other side, in the horizontal bars of the assessment report, the normality reference is the center of the green area, but the border of such areas corresponds to a tolerance degree of normality deviation, which varies for each feature. Furthermore, this report allows either the comparison of a subject within a group witsh similar anthropometric features or even of the patient's current state with his condition in previous evaluations.

## IV. CONCLUSION

Jaw-tracking using MEMs sensors has shown to bring more kinematic features of the mastication for the health-care professional, such as minimum, median, and maximum cycle time chewing side preference values, as well as, the minimum, median, and maximum range of motion. The discomfort to chew food during the experiments, when referred, is compatible to the one experienced with the traditional evaluation methods, which adds an inevitable bias to the examination. In future works, in order to minimize such bias, we will validate this novel approach with a wireless system in patients during rehabilitation. Furthermore, the proposed method can be easily implemented as a small-size, low-cost and high-performance system, such that a wearable device can be applied in small ambulatories and not only be limited to laboratory environments.

Based on our experiments, SOM and K-Means, unsupervised learning algorithms, have presented excellent performance to process Jaw-movements data, showing encouraging results and potential to bring a full assessment of the masticatory function. In particular, K-Means provides the concept of normality area, which is a new feedback for the therapist, allowing to track the mastication rehabilitation performance. To enable the use of our approach as real-time feedback, our algorithm must be improved since it groups the data based on a predetermined sample.

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