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Analysis of a New Toothbrushing Technique through Plaque Removal Success

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Abstract

Background/Aims: Determining the levels of oral health and the quality of dental care are fundamental to building concepts of oral health. This study aims to assess toothbrushing techniques using a technical and physical model, clarifying how children and pre-adults learn to brush their teeth. **Materials and Methods:** Data were recorded from 23 participants, both male and female of various ages, using a proposed electronic toothbrush equipped with X-Y-Z axes pathways. The data, collected before and after training experiments, were processed with MATLAB to generate plots for the three axes. **Results:** The study revealed that most parameter values, such as Mean Difference Between Amplitudes (MAV, 6.00), Wilson Amplitude (WAMP, 179.419), and Average Amplitude Coupling (AAC, 1.270), decreased from before to after the experiments. Furthermore, the average overall epoch lengths (AVG) showed a 75% reduction in movement amplitude between the two experiments. **Conclusion:** Dentist observations indicated which brushing methods were acceptable or not. Analytical values suggest that individuals learn the toothbrushing technique effectively, and medical observations clearly demonstrate the success of the proposed method.

Keywords

Techno-Physical Toothbrushing, Oral Hygiene Education, Dental Technology, Plaque Analysis

1. Introduction

Oral diseases present a significant global health challenge, especially among children. Zareban *et al.* suggest that oral health education should emphasize student groups more heavily [1]. A major obstacle in dental practice is the lack of a visible, objective index to assess patients' toothbrushing movements. Chua *et al.* highlighted the inconsistency in opinions regarding when children are ready to brush independently [2]. Their research introduced a multifactorial model showing that chronological age and motor development are key predictors of a child's ability to brush effectively. Research by Otsuka *et al.* indicated that manual toothbrushes are predominantly used [3], but their study also found that these toothbrushes alone are inadequate for interproximal cleaning. In a cross-sectional study, Almaghaslah demonstrated that community pharmacists have the necessary knowledge and attitude to offer dental care counseling [4], suggesting their potential role in oral health development programs. Tadakamadla *et al.* explored the relationships between child and family socio-demographic factors and the context of toothbrushing [5], finding a connection between twice-daily brushing and certain parenting and child behaviors. Alwadi's research highlighted a significant gap in clinical focus, particularly regarding children with disabilities [6], whose perspectives are often overlooked in oral health research. This omission impedes a comprehensive understanding of oral health issues. Leme *et al.* investigated basic and daily oral hygiene care for adults with special needs [7], emphasizing the importance of such care in maintaining oral health. Their findings revealed a range of emotions among caregivers, from feelings of failure to the use of creative strategies. De Sam Lazaro *et al.* advocated for competency-based education in oral health as a way to address oral health outcomes and equity issues [8], noting the potential of asynchronous webinars in enhancing oral health knowledge among health professionals. Gennai *et al.* evaluated the efficacy of different oral hygiene protocols in periodontitis patients [9], finding that interdental brushes and rubber picks were more effective than toothbrushing alone. Hanafy and Abdelmoniem assessed the impact of an oral health education program on Egyptian children [10], observing significant improvements in their oral health status.

The potential of electronic toothbrushes in enhancing oral hygiene practices has been increasingly recognized. Studies by Dhir and Kumar [11], as well as Grender *et al.* and Adam *et al.* [12] [13], have demonstrated the superiority of powered toothbrushes over manual ones, highlighting the effectiveness of micro-vibrations in plaque removal. Moreover, Thomassen *et al.* conducted a meta-analysis advocating for the use of powered toothbrushes for daily plaque removal [14]. Adam introduced the Oral-Bio electric toothbrush, underscoring its plaque removal efficacy [15]. Wolf *et al.* investigated the influence of brushing habits on effectiveness, using the MT system to track toothbrush position and orientation [16]. These findings suggest a promising avenue for technological advancements in dental care, particularly in the development and assessment of novel toothbrushing techniques.

Despite these advancements, the literature lacks a comprehensive understanding of how different demographics, especially children and pre-adults, learn and adopt new toothbrushing techniques. Our study aims to fill this gap by assessing a novel toothbrushing model that employs a technical and physical approach to elucidate the learning process across various age groups. This model, leveraging an electronic toothbrush equipped with X-Y-Z axes pathways, aims to provide a clearer insight into the effectiveness of brushing methods, thereby contributing to the development of more effective oral health education programs and brushing techniques.

In light of these findings and the recognized need for improved oral hygiene techniques, our study posits the hypothesis that a novel toothbrushing technique, characterized by a techno-physical model capable of tracking movements in three dimensions, will significantly enhance plaque removal efficiency and oral health across various age groups, compared to traditional methods. This hypothesis stems from the premise that a precise, data-driven approach to toothbrushing can overcome the limitations of current practices by offering tailored guidance and feedback, thus facilitating more effective learning and execution of oral hygiene routines.

Our study aims to assess the efficacy of brushing methods using a novel model. This model serves as an analytical technique to evaluate the efficiency and performance of toothbrushing techniques, aiding in teaching optimal toothbrush use. It is a multiphase optimization application designed as a data analyzer, capable of previewing and detecting three-axis toothbrush motions. Its primary function is to meticulously track, stabilize, and standardize toothbrush motion in an equilibrium position across the X, Y, and Z axes.

2. Materials and Methods

In this study, we developed a mechanical and physical model to elucidate the learning process of toothbrushing for both adults and children. A major innovation introduced in this research is the Modified Multidirectional toothbrush, which features an array of retractable heads and handles designed to adapt to various oral geometries and brushing styles. This toothbrush is equipped with a sophisticated electronic device that captures toothbrush movements along the X-Y-Z axes, thereby enabling detailed analysis of brushing techniques.

2.1. Toothbrush Description

The Modified Multidirectional toothbrush incorporates various retractable types of heads and handles, facilitating a customized brushing experience that addresses individual needs and preferences. The toothbrush's design, developed using Fusion 360, 3ds Max, and SolidWorks, emphasizes ergonomics and efficiency in plaque removal. Prototypes were constructed from FDA-compliant materials such as polyethylene, polypropylene, and synthetic nylons (Nylon 6/12, Nylon 11, Nylon 12), ensuring safety and durability (**Figure 1**). The second key innovation relates to the analysis application of our Modified Multidirectional toothbrush's electrical device. This comprises a three-axis motion com

Figure 1. Proposed system configurations. (a) Digital 3D design of proposed prototype. (b) Sample of proposed prototype. (c) Integrated sample with Arduino. (d) Data analyzer Integrated 6 Axis, Buzzer.

ponent system, incorporating various microprocessors including an Arduino-Nano, an MPU6050 Integrated 6 Axis sensor, a buzzer, and an SD card storage module (Figure 1(d)).

The MPU6050 is a sophisticated Motion Tracking device that combines a 3-axis gyroscope with a 3-axis accelerometer. It incorporates a Digital Motion Processor (DMP) capable of executing complex 6-axis Motion Fusion Algorithms. This design is tailored to meet the high-performance requirements of smartphones, offering benefits such as low power consumption, cost-effectiveness, and compatibility with both tablets and wearable sensors. Furthermore, the MPU6050 is designed to facilitate interaction with various non-inertial digital sensors, such as pressure sensors, through its auxiliary I2C port [17]. The secondary significant electronic advancement in our Multidirectional Therapeutic Toothbrush is the integration of key elements necessary for three distinct types of axis motion. These include the Arduino Nano, MPU6050 Integrated 6 Axis, Buzzer, and SD card storage module, forming the core of the toothbrush's advanced functionality.

2.2. Experimental Methodology

A total of 23 individuals, including 7 females and 16 males of various ages, were recruited for this study. Participants were selected based on specific criteria to ensure a representative sample of the population. The age range of participants was from 6 to 65 years, encompassing children, adolescents, and adults. The oral health status of participants prior to the study was documented, with inclusion criteria requiring at least a basic level of oral hygiene but presenting opportunities for improvement in brushing techniques. Baseline brushing habits were assessed through a questionnaire, with particular attention to frequency, duration, and method of brushing.

Ethical clearance for the study was obtained from the Yıldız Technical University Social and Humanities Research Ethics Board. Participants were voluntary patients associated with Hayat Medical Clinics in Istanbul, Türkiye. Before the commencement of the study, each participant signed an informed consent form, which outlined the experiment's goals, potential risks, and confidentiality protocols. Steps are outlined as in **Figure 2**.

The initial step of the experiment involved connecting a USB data cable from the computer to the toothbrush detection device. Each participant's session began with calibrating the toothbrush detection device individually. The participants were then individually called to perform the experiment in a controlled environment, which was maintained at a standard temperature of 25˚C, free from extraneous noise, and with attention to physical comfort. An alarm system was used to indicate the device was in standby mode, signaling the participants to start using the brush device. In the first part of the experiment, the brushing device did not provide auditory alerts to the participant but rather recorded the data of the brushing paths onto an SD card. Each brushing session lasted approximately 2 to 3.5 minutes. The device, powered by an ARDUINO-NANO, stored the collected data and saved it in Log and txt file formats on an SD memory card. This procedure was repeated with each participant, ultimately involving a total of 23 subjects. The collected data were then analyzed using statistical software, including Excel and MATLAB 2022b. The results were presented in the form of tables and graphs for a thorough assessment and evaluation during the discussion phase of the study.

2.3. Data Analysis

The data collected in this study is processed using MATLAB to visualize the three-axis movements, which include the X, Y, and Z axes, as illustrated in **Figure 3**. This experimental procedure was consistently applied across all participants, resulting in data from a total of 23 subjects, each with a sequence length of 10,000. The data, recorded both before and after the educational phase for each of the 23 subjects, are segmented into epochs. Each epoch comprises 10,000

Figure 2. Clinical experiment preparation.

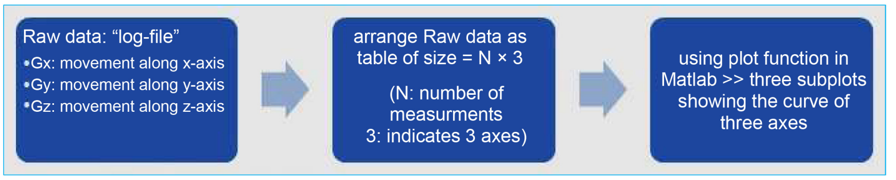

Figure 3. Schematic of process via MATLAB.

samples. For each epoch, 13 distinct parameters (or features) are calculated and recorded in a format denoted as XXX (epc, sbj, exp), where XXX represents the specific extracted parameter.

Subsequently, the average value over the length of each epoch is computed to summarize the data, and this average is recorded as AVG_XXX (sbj, exp). Here, AVG_XXX signifies the average of the specified parameter over the length of the epoch for each subject and experiment. It is important to emphasize that the effectiveness of any pattern classification system in identifying patterns greatly depends on the selection of features that characterize the raw signals. This highlights the importance of careful feature selection to ensure accurate and meaningful analysis of the data.

In this study, various feature parameters were identified based on the amplitude and frequency characteristics of the signals. These characteristics are advantageous as they can be calculated directly without requiring any conversion process, facilitating the ease of processing real-time signals. The features utilized in this study are detailed individually, with references provided for each [18]-[26]. The parameters employed are listed and elaborated upon in **Table 1**.

3. Results and Discussion

The tables presented below showcase the raw data from each subject, divided into epochs of 10,000 samples each. The total number of feature parameters is determined by the quantity of temporal segments within each pattern. Despite significant temporal structural variations in the signals, pattern recognition is feasible due to the statistical consistency of the waveforms. The frequency values acquired indicate that the selected parameters are specifically designed for the proposed model. This model acts as a data analyzer, assessing and identifying the three-axis movements (X, Y, and Z axes) of the toothbrush motion trajectories. These trajectories are analyzed and characterized using statistical methods through our innovative Multidirectional Therapeutic Toothbrush (MTB), which functions as a multifaceted optimization application (MOA). The raw data for each subject was segmented into epochs, with computations performed for each epoch. Data storage was organized for each subject and experiment to highlight variations in patterns across different trials. The feature parameters used are based on both temporal and spectral statistics. A MATLAB statistical application processes the data, producing visual representations of the toothbrush movements across the three axes. After data processing, the statistical values confirm that data from 23 subjects were recorded both before and after the educational phase.

Table 1. Statistical of feature parameters.

	Statistical Feature	Formula
1	Wilson Amplitude (WAMP): This is the number of times that the difference between two consecutive amplitudes exceeds a certain threshold. $T = 0.05$.	$\text{WAMP} = \sum_{i=1}^{N} u\left(\lvert x_{i+1} - x_i \rvert - T\right)$
2	Zero Crossing (ZC): ZC represents the number of times that the amplitude of the signal passes through zero. Because the arithmetic of the ZCR is uncomplicated and easy to implement. The ZCR is defined as the number of zero-crossings in a fixed data length. A threshold must be included in the ZCR calculation to reduce the zero-crossings induced by measurement noise.	$\text{ZC} = \sum_{i=1}^{N-1} u\left(-x_i x_{i+1}\right)$
3	Mean of Amplitude (MAV): This feature determines the mean of the difference in amplitudes of two consecutive samples.	$\text{MAV} = \frac{1}{N} \sum_{i=1}^{N} \lvert x_i \rvert$
4	Mean Frequency (MNF): This feature estimates the mean frequency of the signal in a time segment. MNF is the average frequency value obtained by dividing the power spectrum density values of each frequency of the signal and the multiplication of the frequencies by the total power spectrum density. The h_i value refers to the frequency value in the *i*-frequency spectrum, and f_i likewise refers to the power spectrum.	$\text{MF} = \frac{\sum_{i=1}^{N} h_i f_i}{\sum_{i=1}^{N} h_i}$
5	Median Frequency (MDF): MDF is the frequency value in the middle of the two halves of the spectrum. The median in the spectrum is known as the frequency.	$\text{MDF} = \sum_{j=1}^{\text{MDF}} P_j = \sum_{j=\text{MDF}}^{M} P_j = \frac{1}{2} \sum_{j=1}^{M} P_j$
6	Variance (VAR): In the stochastic process, variance characterizes the average power of a random signal and can be explained as follows.	$\text{VAR} = \frac{1}{N-1} \sum_{i=1}^{N} x_i^2$
7	Average Amplitude Coupling (AAC): The AAC parameter is considered equivalent to the wavelength (WL) value of the signal, except that the wavelength of the signal is averaged.	$\text{AAC} = \frac{1}{N} \sum_{i=1}^{N-1} \lvert X_{i+1} - X_i \rvert$
8	Difference Absolute Standard Deviation (DASD): This parameter's value is similar to the RMS characteristic, in other words, it is the standard deviation value of the wavelength.	$\text{DASDV} = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} \left(X_{i+1} - X_i\right)^2}$
9	Wavelet Length Power (WL): this statistical feature is based on computing the Euclidian length of the waves within the time series.	$\text{WL} = \frac{1}{N} \sum_{i=1}^{N-1} \lvert X_{i+1} - X_i \rvert$
10	Log value (LOG): This parameter computes the natural logarithmic of particular time series.	$\text{LOG} = \mathrm{e}^{\frac{1}{N} \sum_{i=1}^{N} \log \lvert X_i \rvert}$
11	Slope Sign Change (SSC): It is another method to represent the frequency information of the signal. To avoid background noise in the signal by changing the sign of the signal slope several times, the positive and negative slopes between three consecutive segments are determined by using the threshold function to determine the number of changes.	$\text{SSC} = \sum_{i=2}^{N-1} \left[f\left(X_i - X_{i-1}\right) * \left(X_i - X_{i+1}\right) \right]$; $f(X) = \begin{cases} 1, & \text{if } X \geq \text{threshold value} \\ 0, & \text{otherwise} \end{cases}$
12	Root Mean Square (RMS): It is the effective value of the amplitude values of a signal. As expressed in Equation, it means the square root of the average of the squares of the values of the N-length X signal at point *i*. Numerical values containing the RMS and standard deviation (SD) characteristics of the signal at the time of contraction increase significantly. The RMS is also known as the quadratic mean and is a particular case of the generalized mean with exponent 2.	$\text{RMS} = \sqrt{\frac{1}{n} \sum_{i} x_i^2}$
13	Standard Deviation (SD): A standard deviation (or σ) is a measure of how dispersed the data is in relation to the mean. Low, or small, standard deviation indicates data are clustered tightly around the mean, and high, or large, standard deviation indicates data are more spread out.	$\sigma = \sqrt{\frac{\sum \left(x_i - \mu\right)^2}{N}}$

Table 2 illustrates the sample lengths for Experiment 1 related to Subject 12, categorized according to the teaching mode of the experiment, labeled as the "BEFORE-Teaching the subjects" phase (BTE). Correspondingly, the sample lengths for Experiment 2 are determined based on the experiment's teaching mode, termed the "AFTER-Teaching the subjects" phase (ATE).

The raw data from each participant were divided into epochs, with specific calculations carried out for each epoch. Storage was organized for each participant and experiment to demonstrate the differences in patterns across various trials. The feature parameters used in this analysis are based on both temporal and spectral statistics. Table 3 displays the sample lengths for Experiment 1, categorized according to the experiment's teaching mode, referred to as the "BEFORE-Teaching the subjects" phase (BTE). In a similar manner, the sample lengths for Experiment 2 are identified based on the teaching mode of the experiment and are labeled as the "AFTER-Teaching the subjects" phase (ATE).

By analyzing the movement signals along the X, Y, and Z axes, we can pinpoint specific locations where the toothbrush exhibits consistent motion signals. Figure 4 clearly illustrates this, with the top part showing Gy and the bottom part displaying Gx, Gy, Gz. The figure highlights the amplitude range observed after the experiment, thereby underscoring the effectiveness of our model. This

Table 2. Sample of subject 12 before training (Sign. of Expt.-1).

X	Y	Z
−41.94808936	11.90797384	−1.220817486
−44.28004112	12.56454576	−1.334233317
−46.0085945	13.04862177	−1.439652039
−47.13485648	13.36056033	−1.536482589
−47.68830512	13.50880682	−1.624674918
−47.72393569	13.50907947	−1.704686482
−47.31796842	13.38314606	−1.777416816
−46.56243214	13.15728069	−1.844115572
−45.55900662	12.86050981	−1.906271321
−44.41254673	12.52276775	−1.965489778
−43.22472184	12.17308505	−2.023370837
−42.08818317	11.83792693	−2.081393747
−41.06643896	11.53587342	−2.136840314
−40.23339584	11.2877032	−2.194067168
−39.63147009	11.1055348	−2.25410769
−39.28245372	10.99559868	−2.317743057
−39.18790709	10.95835012	−2.385477442
−39.33084749	10.98895198	−2.457528801
−39.67854467	11.07807347	−2.533834488

Table 3. Sample of subject 12 before training (Sign. of Expt.-2).

X	Y	Z
−2.301394199	0.780472815	28.99756691
−2.613336625	0.892882595	32.81480087
−2.546079227	0.875836873	31.82536557
−2.321406323	0.800484939	28.88750023
−2.172081428	0.744804639	26.99522468
−2.192880534	0.744497312	27.35521937
−2.311400261	0.780472815	29.01757903
−2.391422134	0.809696234	30.20470028
−2.370901596	0.809961732	30.07606844
−2.291388137	0.790478877	29.13765177
−2.23223549	0.77296058	28.42133288
−2.239839523	0.771369548	28.55380594
−2.291388137	0.780472815	29.26773058
−2.329000334	0.785411381	29.8107615
−2.328766629	0.782559356	29.80947435
−2.311400261	0.780472815	29.44783969
−2.309754981	0.788355569	29.10731975
−2.343941804	0.810377274	29.05992614
−2.401454817	0.840509186	29.21770027

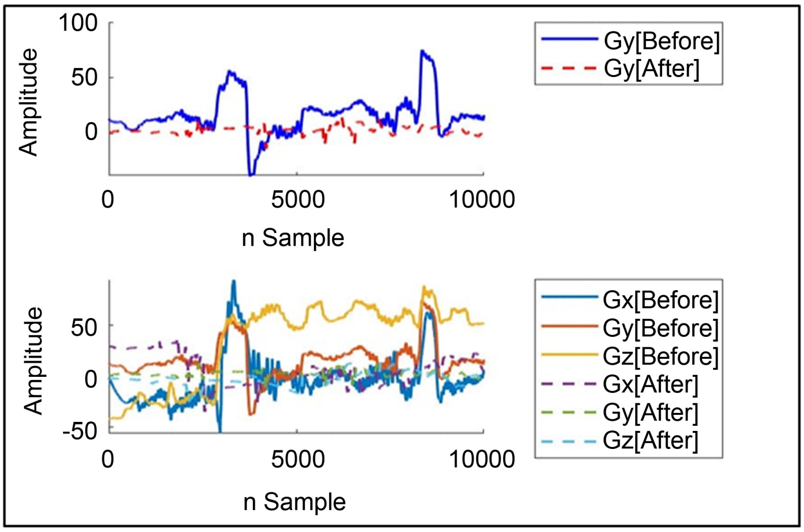

Figure 4. Subject 12 mean and median frequency spectrum of BEFORE and AFTER experiments.

analysis is crucial as it helps generate a comprehensive feature set to accurately represent each pattern's behavior. The statistical analysis includes data from 23 subjects, recorded both before and after the educational phase with the proposed electronic equipment. An analysis of the recorded frequency, including Mean and Median components, using this equipment suggests a decrease in the instability of toothbrush use post-implementation of the learning model.

It is important to emphasize that the primary goal of using the proposed electronic equipment as a data analyzer is to monitor, stabilize, and standardize the toothbrush's motion in a balanced position across the three axes (X, Y, and Z). The orientations for these movements have been meticulously established and fine-tuned using statistical analytical methods. This process involves the use of our newly developed Multidirectional Therapeutic Toothbrush (MTB) as a multifaceted optimization application (MOA).

The comparison of clinical features shown in **Figure 5** clearly reveals a distinct difference between the results from the BEFORE and AFTER experiments. This stark contrast aligns closely with the data obtained from our experimental model. The findings conclusively show that there was a significant reduction in plaque accumulation and tooth staining after using our model, thereby highlighting its effectiveness. This comparison underscores the success of the model in improving oral hygiene practices, as evidenced by the tangible clinical outcomes.

Table 4 presents a subset consisting of 10,000 samples. In this study, the raw data from each participant were segmented into epochs, and specific calculations were carried out for each of these epochs. Additionally, the data were organized and stored for each participant and experiment. This organization was crucial for illustrating the variations in brushing patterns observed across different trials. To accurately represent the behavior of each pattern, feature parameters derived from both temporal and spectral statistics were utilized. These parameters were instrumental in creating a comprehensive feature set that effectively captures and describes the unique characteristics of each pattern observed in the study.

The data from this study is currently being analyzed in MATLAB to evaluate the movement across the X, Y, and Z axes, utilizing the proposed electronic equipment as a data analyzer. This process is exemplified in **Table 5**. Upon the

Figure 5. Second phase demonstrate a high degree of tooth plaque-staining cleaning.

Table 4. Sample of subject 16 before training (Sign. of Expt.-1).

X	Y	Z
20.47370964	37.60518125	−7.024703895
21.60125899	39.65991027	−7.433496856
22.43265638	41.16577309	−7.74537656
22.96884708	42.12410686	−7.960453735
23.22470386	42.56191051	−8.083509826
23.22760597	42.52925438	−8.123534213
23.01531166	42.09539208	−8.093021954
22.63327985	41.34385859	−8.007083462
22.13163015	40.36690088	−7.882429107
21.56195031	39.25962277	−7.73629887
20.97416501	38.11423552	−7.585409098
20.41366944	37.01478591	−7.444985325
19.91107184	36.02112871	−7.323068995
19.50270114	35.19849751	−7.23379065
19.20906731	34.58526722	−7.184295072
19.0405121	34.2010931	−7.178370686
18.99742288	34.04728108	−7.216492522
19.07108406	34.10833469	−7.296073893
19.24507197	34.35450655	−7.411897668

completion of the data processing phase, the statistical values reflect the recorded data from 23 participants, encompassing both the period before and after the educational phase of the experiment. **Table 5** specifically displays the sample lengths for Experiment 1, categorized according to the teaching mode of the experiment, and is labeled as the "BEFORE Teaching the subjects" phase (BTE). In a similar manner, the sample lengths for Experiment 2 are determined based on the teaching mode of the experiment and are defined as the "AFTER-Teaching the subjects" phase (ATE). This data is crucial for evaluating the effectiveness of the educational intervention in improving the toothbrushing techniques of the subjects.

The analysis of movement signals across the three axes (X, Y, and Z) enables the identification of specific locations where the toothbrush exhibits consistent motion signals. This is clearly evidenced in the data. **Figure 6**, in particular, illustrates the amplitude range observed in the AFTER-experiment phase. In this figure, the top part represents Gy, while the bottom part displays Gx, Gy, Gz. Such a representation effectively demonstrates the advantages of our model.

The analysis of the Mean and Median components, particularly in terms of frequency and using the proposed electronic equipment, reveals a decrease in

Table 5. Sample of subject 16 before training (Sign. of Expt.-1).

X	Y	Z
−2.301394199	0.780472815	28.99756691
−2.613336625	0.892882595	32.81480087
−2.546079227	0.875836873	31.82536557
−2.321406323	0.800484939	28.88750023
−2.172081428	0.744804639	26.99522468
−2.192880534	0.744497312	27.35521937
−2.311400261	0.780472815	29.01757903
−2.391422134	0.809696234	30.20470028
−2.370901596	0.809961732	30.07606844
−2.291388137	0.790478877	29.13765177
−2.23223549	0.77296058	28.42133288
−2.239839523	0.771369548	28.55380594
−2.291388137	0.780472815	29.26773058
−2.329000334	0.785411381	29.8107615
−2.328766629	0.782559356	29.80947435
−2.311400261	0.780472815	29.44783969
−2.309754981	0.788355569	29.10731975
−2.343941804	0.810377274	29.05992614
−2.401454817	0.840509186	29.21770027

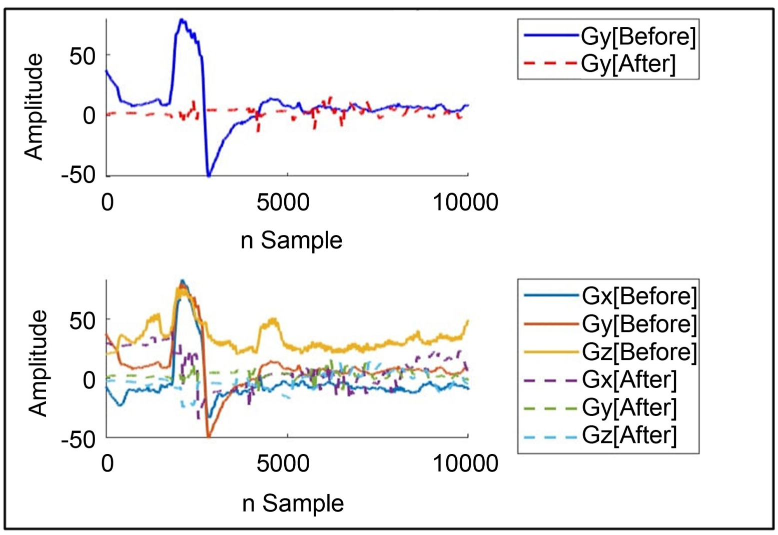

Figure 6. Subject 16 mean and median frequency spectrum of BEFORE and AFTER experiments.

these values. This decrease is indicative of improved stability in toothbrush usage after participants have undergone the learning model. This suggests that the model is effective in enhancing the brushing technique, as evidenced by the more stable and consistent toothbrush movements post-educational phase. Such findings underscore the value of the learning model in promoting better oral hygiene practices.

The clinical features displayed in **Figure 6** distinctly showcase the noticeable differences in oral health conditions before and after the experiment. This comparison strongly supports the alignment with the data obtained from our modeling. The figures clearly illustrate that there was a significant reduction in plaque accumulation and tooth staining as a result of the experiment. These findings effectively highlight the distinct advantages of our proposed model. The substantial improvement in oral health, as evidenced by the reduced plaque and staining, underscores the effectiveness of our model in enhancing toothbrushing techniques and, consequently, oral hygiene.

Figure 7 illustrates that a significant number of parameter values show a decrease between the before and after experiments. Metrics such as the Mean Absolute Value (MAV) are particularly notable. MAV measures the average difference in signal amplitudes or the rate of amplitude fluctuation. These calculations are performed separately for each subject and experiment. This data is crucial for highlighting the variations in brushing patterns across different trials.

The subsequent feature parameters, which exhibit stability in both temporal and spectral statistics, are used to create a comprehensive feature set. This feature set is essential for accurately describing the behavior of each brushing pattern.

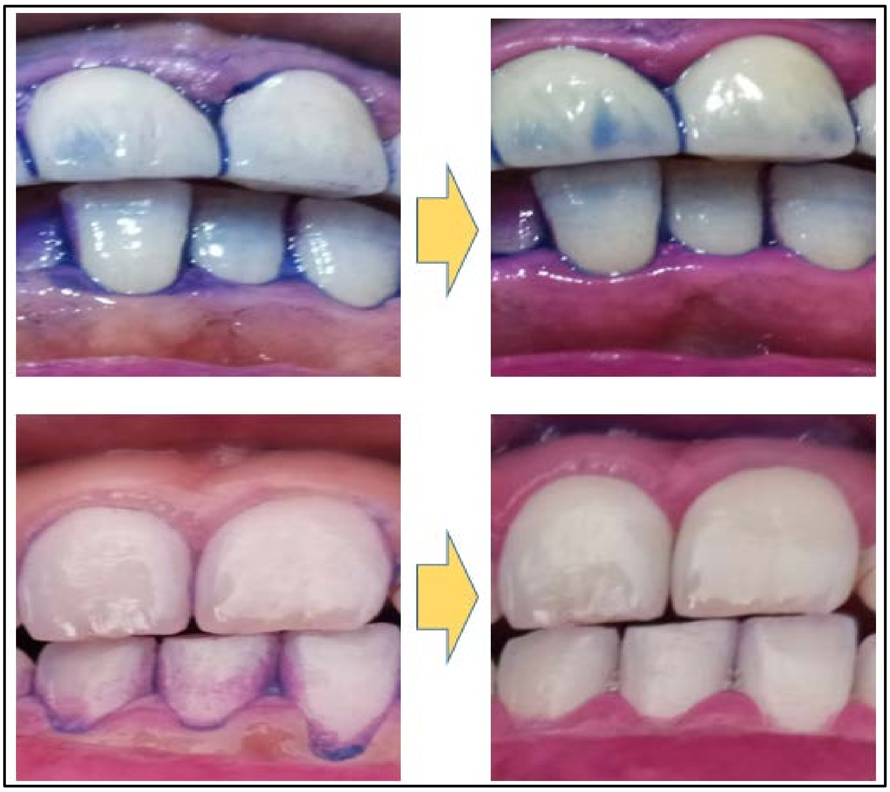

Figure 7. The second phase illustrates a notable efficacy in the removal of tooth plaque staining.

The effectiveness of these parameters in representing the patterns is clearly visualized in Figure 8. The visualization in Figure 8 provides a clear representation of how these parameters contribute to understanding the nuances of brushing behavior, further validating the efficacy of the model and its applicability in enhancing toothbrushing techniques.

According to Table 6 and Figure 8, there is a clear trend of decreasing values in various parameter measurements from before to after the experiments. Notably, the Mean Difference Between Amplitudes (MAV) is indicated to be 6.00,

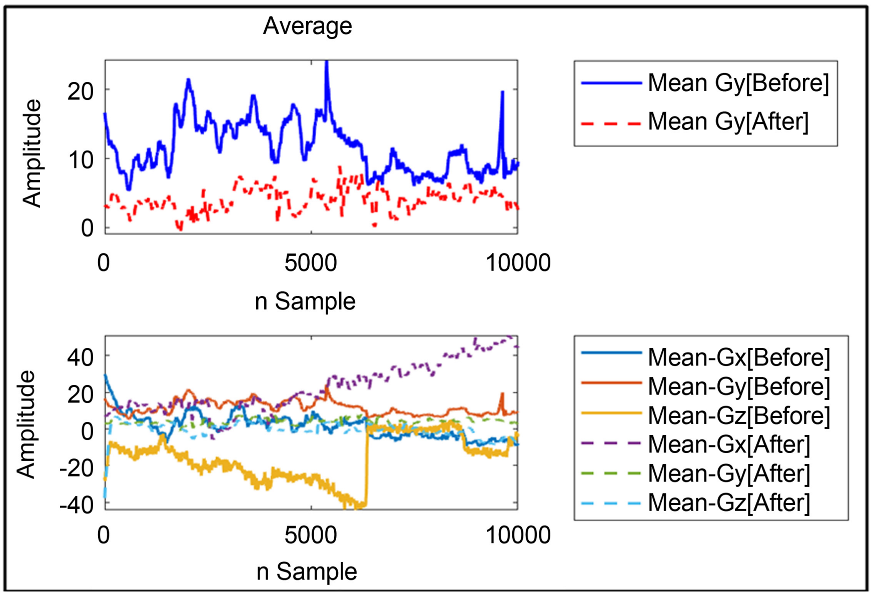

Figure 8. The average mean and median frequency spectrum of BEFORE and AFTER experiments.

Table 6. Averaging values across subjects is done to reduce dimensionality.

Parameter	Exp1-Before	Exp2-After
MAV	8.562	6.00
RMS	11.473	8.00
MNF	0.086	0.071
MDF	0.034	0.021
AAC	1.757	1.270
WAMP	202.812	179.419
DASD	3.326	2.071
ZC	18.585	23.160
WL	1.761	1.272
LOG	5.377	2.688
VAR	392.908	78.829
SSC	129.643	110.565
SD	9.545	4.914

Wilson Amplitude (WAMP) is 179.419, and Average Amplitude Coupling (AAC) is 1.270. Additionally, the Variance (VAR) is recorded at 78.829, and the Standard Deviation (SD) is approximately 4.914. These values illustrate the average variances between the amplitudes and the rate of signal amplitudes.

The observed decline in these values suggests a positive impact from learning the correct toothbrushing technique. Specifically, it implies an optimization in controlling the force orientations (pathways) applied to the toothbrush. This improvement is a significant indication of the effectiveness of the educational phase of the experiment in enhancing toothbrushing skills.

Other parameters, such as the Mean Frequency (MNF) and Median Frequency (MDF), which are 0.071 and 0.021 respectively, show changes in frequency components. The reduction in these mean and median frequency components is indicative of increased stability in using the proposed toothbrush following the implementation of the learning mode.

Furthermore, an average reduction in amplitude between the two experiments is noted, which falls within the range of approximately 75%. This substantial reduction further underscores the success of the educational intervention in improving the efficiency and effectiveness of toothbrushing techniques as demonstrated by the participants in this study.

Figure 9 provides a clear illustration of the effectiveness of our model, which employs the proposed electronic equipment to meticulously record data for each participant. This data is divided into epochs, and detailed calculations are performed for each epoch. The data is then systematically stored for each participant and experiment, serving to highlight the variations in brushing patterns across different trials. This approach is crucial for understanding the nuances and changes in brushing behavior.

The feature parameters used in the analysis are based on both temporal and

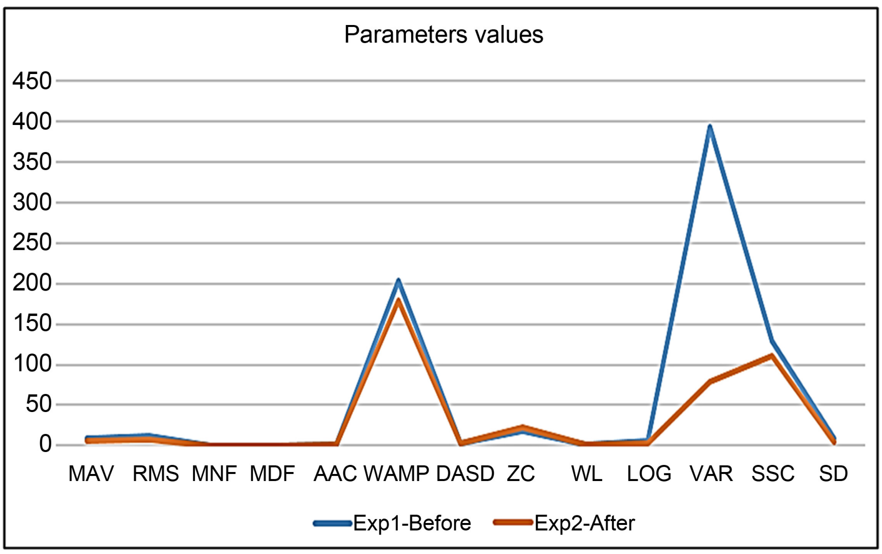

Figure 9. The average mean and median frequency spectrum of BEFORE and AFTER experiments.

spectral statistics. As shown in **Figure 9**, the amplitude range observed in the AFTER experiment particularly emphasizes the benefits of our model. The reduction in a majority of parameter values from before to after the experiments is a key observation. Metrics such as the Mean Absolute Value (MAV), which calculates the mean difference between signal amplitudes or the rate of fluctuation, play a vital role in this context. These metrics contribute to forming a comprehensive feature set, essential for accurately representing the behavior of each brushing pattern.

The decrease in parameter values like MAV and others indicates an improvement in brushing techniques, likely resulting from the educational phase of the experiment. The amplitude range displayed in the AFTER experiment demonstrates the model's capability in enhancing toothbrushing efficiency and effectiveness, reaffirming the value of the proposed model in improving oral hygiene practices.

The comparison of various parameters as illustrated in **Figure 9** reveals a general trend of decreasing values from the before to the after experiments. This trend is particularly evident in metrics such as the Mean Absolute Value (MAV), which measures the mean difference between the amplitudes of the signal or the rate of fluctuation. The observed decrease in MAV can be attributed to the impact of learning the correct toothbrushing technique. Essentially, this decrease signifies not just an improvement in brushing method but also reflects the optimization of pressure force exerted on the toothbrush.

In addition to MAV, other parameters like the Mean Frequency (MNF) and Median Frequency (MDF) demonstrate changes in the range of frequency components between the two experiments. These alterations in frequency components are indicative of the changes in brushing dynamics post-educational intervention. The differences in MNF and MDF values suggest that the participants were able to modify their brushing technique in a way that resulted in more effective and efficient brushing patterns.

Overall, the data presented in **Figure 9** underscores the effectiveness of the educational phase of the experiment. It shows that participants were able to learn and apply a more optimal toothbrushing technique, which is reflected in the improved parameter values post-experiment. This improvement not only indicates better brushing habits but also points to the potential long-term benefits in oral health through the use of the proposed toothbrush model.

4. Conclusions

The experiment demonstrates a correlation between the irregularity of tooth brushing movements and the persistence and buildup of bacterial plaque. Conversely, regularity and stability in brushing movements are associated with reduced plaque accumulation. This relationship is highlighted by the sensitivity of the alert system in the proposed electronic toothbrushing equipment, which effectively records and reflects a dentist's clinical observations (Before and After) to assess whether the brushing methods are acceptable or not.

Key findings from the experiment include:

- Movement Amplitude Reduction: On average, there was a 75% reduction in movement amplitude between the two experiments, indicating a significant improvement in the efficiency and effectiveness of brushing techniques.
- Improved Plaque Removal: The second phase of the experiment clearly demonstrated a higher degree of plaque removal and an overall improvement in oral health compared to the random movements executed by the participants initially.
- Decrease in Collaborative Values: The values representing each parameter decreased, signifying a refinement in brushing movements and techniques.
- Slower, More Deliberate Movements: Participants tended to slow their movements and better understand the brushing technique, resulting in more effective cleaning.
- Inclusivity for Special Needs and Weakened Motor Skills: The equipment and methodology proved beneficial for individuals with special needs and those with weakened motor skills, empowering them to correct their tooth brushing flaws.
- Device as an Optimization and Training Tool: The development of this device focused on optimizing and rectifying inaccuracies in tooth brushing. It also serves as a valuable training tool for children and adults, aiding them in learning and adopting proper tooth brushing techniques.

In summary, the experiment underscores the effectiveness of the proposed tooth brushing model not only in improving oral hygiene practices but also as a means of inclusive oral health education, catering to a wide range of individuals with varying needs and abilities.

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Author Contributions

Elhadi A. A. Shkorfu: Conceptualization, Methodology, Software, Data curation, Writing—Original draft preparation, Investigation, Reviewing and Editing; Serkan KURT: Methodology, Supervision, Data curation, Validation, Writing, Reviewing and Editing; Fatih ATALAR: Supervision, Validation, Reviewing and Editing; Ali OLAMAT: Supervision, Validation, Reviewing and Editing; Aysel ERSOY: Supervision, Validation, Writing, Reviewing and Editing.

Availability of Data and Materials

All data generated or analyzed during this study can be shared by corresponding author when there is a demanding from researchers.

Ethics Approval and Consent to Participate

Ethical approval from the Yıldız Technical University Social and Humanities Research Ethics Board on November 8, 2023, with the identification number 2023.11.

Conflicts of Interest

All authors declare that they have no conflict of interest.

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