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Bruxism: Teeth Grinding Time-Series Episode Detection Through Wearable Sensors

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***Abstract*—This preliminary study uses a fine-tree machine learning algorithm to replicate bruxism biofeedback systems by detecting bruxism episodes using a wearable sensor system. The detection of bruxism grinding was performed among five different resting/sleeping positions--laying on the front, back, left, and right, and sitting up from four participants. A sequence of ten activities (each activity is a combination of sleeping position and grinding or not grinding) was recorded while wearing the wireless sensing system on the front of the chin directly under the mouth. Both time and frequency domain features were extracted from each axis of the wearable sensor system's accelerometer data sets. They were used to determine the presence of teeth grinding with 98% accuracy, and these features were used and experimented with to optimize the classification accuracy of the system.**

Keywords—bruxism, teeth grinding, detection, classification, machine learning

I. Introduction

Bruxism is a condition in which a person grinds or clenches their teeth. It is estimated that between 5 and 20 percent of people suffer from this condition. There are two types of bruxism: awake bruxism, in which the person is awake while grinding their teeth, and sleep bruxism, when the person grinds or clenches their teeth while unconscious. This often leads to irreparable damage to the teeth, persistent headaches, and jaw pain if left untreated [1, 2].

There are many possible causes of bruxism. However, the primary cause of bruxism is most commonly believed to be higher levels of stress or anxiety in one's life [3, 4]. Therefore, one of the logical first steps in treating bruxism is to perform stress-reduction techniques, including but not limited to exercise, meditation, muscle-relaxing medications, therapy, and drug/alcohol/caffeine reduction [5, 6]. This treatment often shows strong results among those with awake bruxism but is not always as effective for those with sleep bruxism. Additional ways to treat bruxism also include wearing a specialized mouth guard to provide a barrier between the upper and lower teeth (most commonly used to treat sleep bruxism) and biofeedback, a method in which a sensor system is worn to detect the levels of grinding and clenching in the mouth and alarm the user when grinding or clenching is detected so the user can respond accordingly, eventually training the user to stop grinding or clenching their teeth [7, 8].

The biofeedback method has its limitations, though – the cost of the system is commonly above $700, and a lack of research has limited the effectiveness of the system [7]. The goal of this research is to recreate and improve upon the biofeedback method with a commercially available wearable sensor system that has been used in other activity recognition tasks [9]-[12], producing one with high accuracy at a fraction of the cost.

II. Methods

The first step was to select a wearable sensor and method of data acquisition. A Mbientlab MetaMotionR unit was selected for use due to its wireless data recording capabilities, compact size, and availability of a 3-axis accelerometer. This device also includes the ability to log data over Bluetooth to an Android or Apple smart device. The axes of the MetaMotionR accelerometers were first determined and kept to the following axis orientation convention, as shown in Fig. 1. Sensor is worn using a mask-like structure that wraps around the chin. The accelerometer data of a subject simulating a series of sleeping positions combined with the grinding and not grinding of teeth was recorded. There were ten stages to the sequence, each performed for 30 seconds. The sequence consisted of the sleeping position and grinding combinations in Table 1. The protocol shown in Table 1 was performed for each data collection trial. The position and the sensor location for the study are shown in Fig. 1. The front center of the jaw was chosen as the sensor location because it is the location of the jaw that is furthest from its instantaneous center of rotation and, therefore, should have the highest acceleration to detect [13]. A sampling

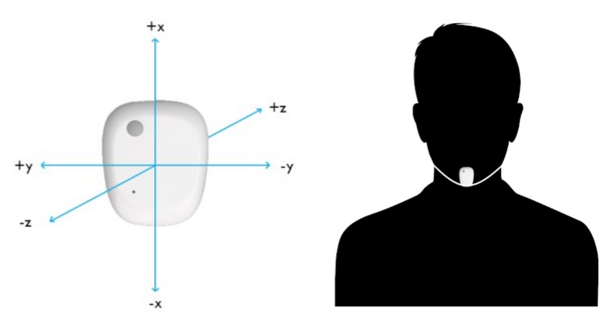

Fig. 1. MetaMotionR orientation reference for the proposed system and Positioning of the sensor for Bruxism detection.

TABLE I. SEQUENCE OF ACTIVITIES PER TRIAL

Stage	Position	Grinding
1	Sitting	No
2	Sitting	Yes
3	Laying on Back	No
4	Laying on Back	Yes
5	Laying on Left	No
6	Laying on Left	Yes
7	Laying on Right	No
8	Laying on Right	Yes
9	Laying on Front	No
10	Laying on Front	Yes

rate of 50 Hz was used to take data from the MetaMotionR 3-axis accelerometer. An example of data for 10 stages are shown in Fig. 2. The data was split up into consecutive windows of 100 samples (2 seconds of data), each window overlapping the previous window by 50%. A total of 27 statistical features were extracted per window. Twelve of these features extracted were in the time domain, and the remaining fifteen were in the frequency domain.

A. Time Domain Features

Twelve time-domain features were extracted from the data sets for classification. The features used for analysis included the means, variances, the 8th root of the variance, and the number of zero-crossings for each window of the x-, y-, and z-axes. Examples of feature clusters are shown in figures 3 and 4.

B. Frequency Domain Features

Fifteen frequency domain features were compiled for classification as well. For each of the x-, y-, and z-axes, Fourier Transforms were used to extract the power of 5 frequency bands. These frequency amplitudes for each frequency band were summed together for each window. The frequency bands initially selected for this experiment were evenly distributed from 1 to 25Hz: 1-5Hz, 6-10Hz, 11-15 Hz, 16-20 Hz, and 21-25 Hz. After initial data collection and analysis, these frequency bands were adjusted to optimize the system.

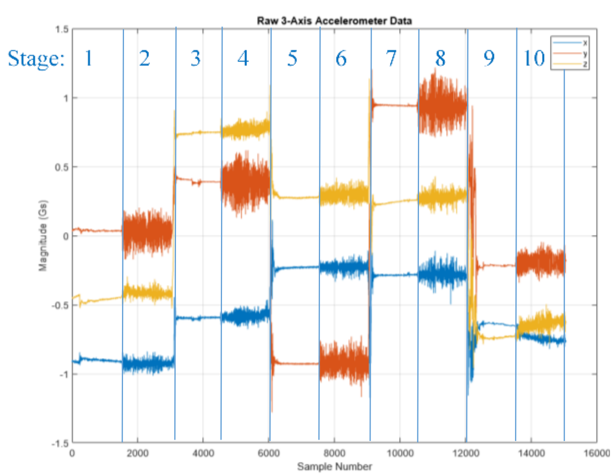

Fig. 2. An example accelerometer data observed from the sensor. Even numbered scenes show instances of bruxism.

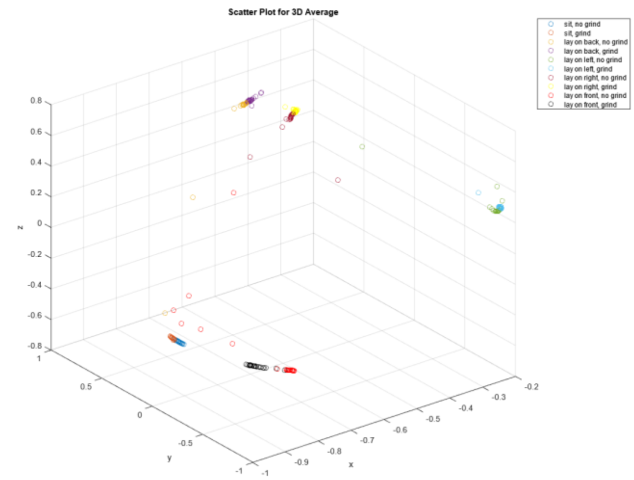

Fig. 3. A scatter plot of mean features extracted from a 3-axis accelerometer data.

These features were calculated in Matlab for each window and entered into a variable array. Each row of this array was also given a class label. Initially, the class labels were provided by activity combination (10 different labels), but then analysis was also performed with only two labels: “grinding” and “not grinding”. This data array was entered into the classification learner tool in Matlab 2021. The Fine Classification Tree was selected as the classification algorithm for this experiment, as it is ideal for classifying data into discrete groups (in this case, the groups being activity labels). The classification learner tool was configured to perform five-fold cross-validation.

III. Results

A. Raw Data and Features

The raw data was collected and entered into Matlab for further processing. An example of the raw data is shown in Fig. 2. The even stages are those with the grinding present, and the odd stages are those without grinding. At first glance, it becomes clear that variance and Frequency Bands will be critical in detecting grinding. The mean values also have robust clustering.

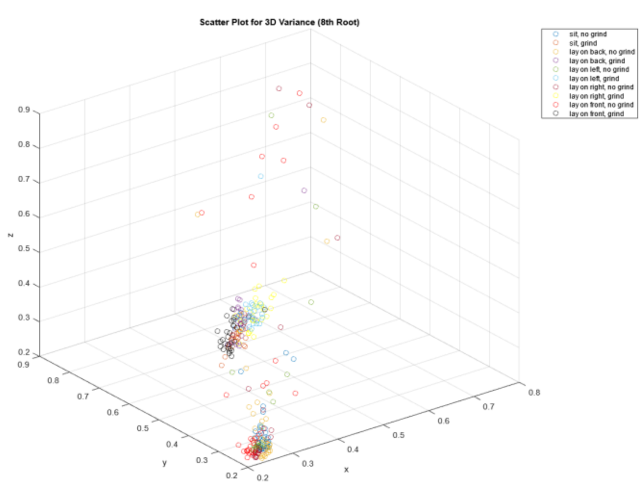

Fig. 4. A scatter plot of the 8th root of variance features extracted from a 3-axis accelerometer data.

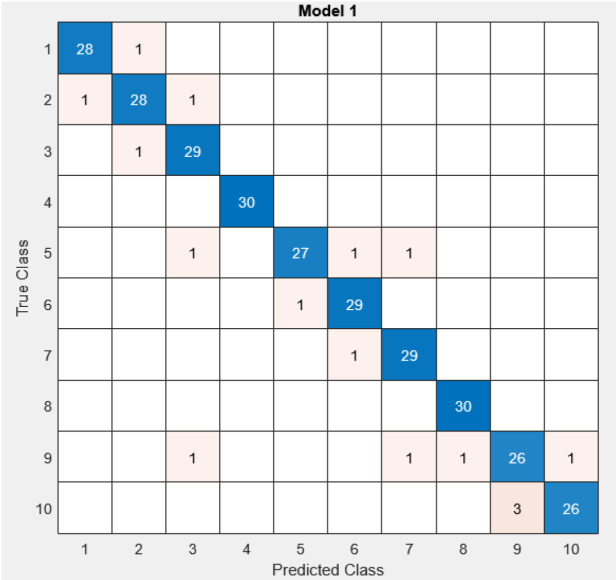

Fig. 5. Initial frequency band power features and its corresponding confusion matrix.

However, there was no significant overlap between griding and not griding with the clusters across participants. The variances are visibly much less readable to the presence of outliers from the transitions. Most of the variance data is tightly clustered around the origin. Zero-crossing features were also extracted and plotted on a 3-D scatter plot. The zero-crossing clusters show significant overlap but are still roughly clustered. The final features examined were the FFT power bands.

B. 10-class Classification Results

The first classification attempt included the following features: Mean, Variance, Zero-crossings, and FFT Bands of 1-5, 6-10, 11-15, 16-20, and 21-25 Hz. This classification attempt used ten classes. The classification matrix for this attempt is shown in Fig. 5.

This initial test returned a 93.6% classification accuracy. Of the 19 misclassifications, 13 were incorrectly classified as grinding or not, and six were classified into classes where an event had a matching "grinding" or "not grinding" attribute.

As the FFT bands show most of the data concentrated at the lower frequencies, the bands were adjusted to extract that data more carefully. The classification algorithm was re-taught with the following FFT power bands: 1-2.5 Hz, 3-5 Hz, 5.5 to 7.5 Hz, 8-10Hz, and 10.5-25 Hz.

This classification attempt returned an accuracy of 94.6%, and 12 of the 16 misclassifications were classified into a class with the wrong grinding presence, as shown in Fig. 6. Other attempts to increase the classification accuracy were not successful.

C. Two-Class Classification Results

Ultimately, only two classes are needed to make this system perform its intended function: "grinding" and "not grinding". For the following experiments, only these two classes were used. However, examining the system with two and ten classes is important to determine the maximum classification accuracy.

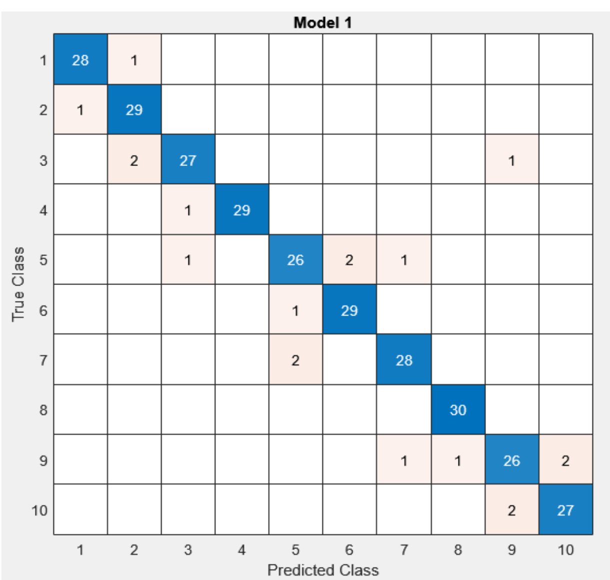

Fig. 6. Classification results showing the adjusted band power features and its corresponding confusion matrix.

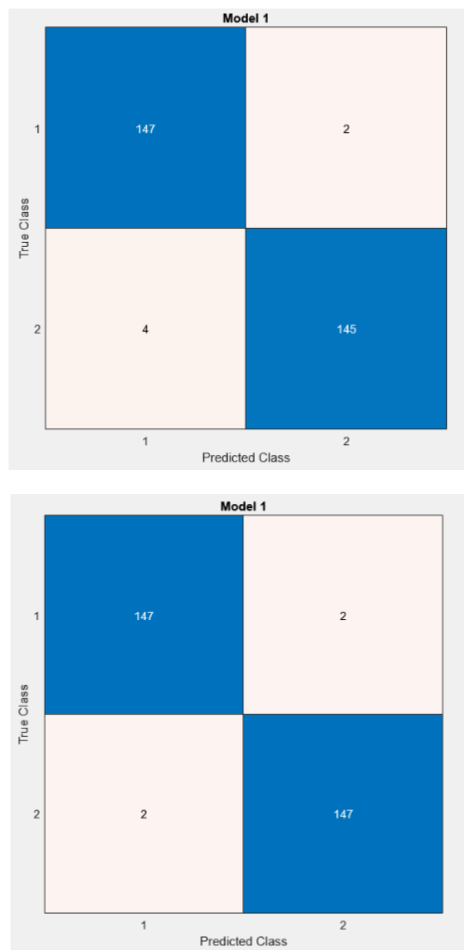

Fig. 7. Two-class classification results using variance as features (top) vs. the 8th root of the variance (bottom).

The first classification attempt used the average, variance, zero-crossings, and newly modified FFT power bands. With only two classes, the classification learner achieved 98% accuracy. The confusion matrix for this attempt is shown in Fig. 7. This 98.0% classification accuracy is a 3.4% increase in accuracy over using ten classes. The 8th root of variance was used as the classification feature, as shown in Fig. 4, instead of the variance extracted from the data to maximize the classification accuracy further. Such an attempt returned a promising 98.7% classification accuracy, with two additional trials correctly classified.

Minimizing the number of operations is desirable for the system to process data in real-time. Therefore, a combination of subsets of features was explored. While most of these combinations showed a drop in classification accuracy, it was found that using variance alone provided a 97.0% classification accuracy, and the 8^{th} root of variance provided a 98% classification accuracy. Such accuracy is possible as the grinding process requires the teeth' movement, which generates periodic oscillatory accelerometer data output. As a result, similar information is observed through calculating variance, while the information can also be obtained in the frequency domain. Since the number of operations for calculating variance is smaller than calculating frequency information, simple use of variance would be preferred over frequency features.

IV. Results Analysis

These results returned very high classification accuracies and a strong case for using such systems. The motion of grinding is detectable with an accelerometer attached to the jaw.

It was found that using only two classes increased the classification accuracy of the system over using ten classes. With the use of only two classes, the algorithm was able to achieve 98.7% accuracy, whereas the 10-class model was only able to achieve 94.6%. However, when the 10-class model disregards the misclassifications classified into a group with the same "grinding" or "not grinding" attribute, this accuracy becomes 96%. Furthermore, this classification algorithm was found to have 98.0% classification accuracy with the 8^{th} root of variance alone. This is critical, as computing resources are often limited for wearable systems, and processing many features can consume a large amount of computing power.

Many of the misclassifications are classified into either the previous or next class. This is likely due to two main reasons: the transitions between each activity are not perfectly timed or instantaneous. For example, when the subject is instructed to transition to the next sleeping position or start grinding, they will not make the transition precisely on time. These transitions also take time to execute. Because the experiment uses a 50% window overlap, each transition is recorded over at least two windows (i.e., one-second duration) or usually more. It is, however, critical to include these transitions between sleeping positions—humans naturally roll over while sleeping. To ensure the classification algorithm does not flag these transitions as grinding, they must be entered into the classifier.

V. Conclusion

The results of this experiment clearly show that grinding is detectable by the classification tree algorithm with a high degree of accuracy. The combination of traits that provided the highest detection accuracy was mean, 8^{th} root of the variance, zero-crossings, and the modified FFT power bands with a 98.7% accuracy when differentiating between only two classes.

With the current data, it is clear that the algorithm has difficulties detecting the differences between rolling over and grinding, as both include periods of high variance. This could create problems for the user as they may be notified that grinding was detected because they rolled over. It may then encourage the user to ignore the alarms, reducing the system's effectiveness on the person's subconscious. Additional data would be helpful to eliminate this, including stationary and dynamic positions while grinding. The transitions between activities included rolling over, but because each transition is captured by 2-3 windows, there is not enough data to create a significant cluster.

Additional features that may be useful in furthering this research may include entropy and cross-correlations, especially as additional data (including rolling over vs. grinding) is taken and analyzed. With the addition of clusters of high variance, other algorithms or types of sensors may also help analyze the data.

In addition, note that the true value of using binary classification is clinically more valuable because physicians and patients are interested in knowing how often and how long the patient grinds teeth. This information is sufficiently provided through binary classification. For further verification, system generalization will be studied with additional data collected from more participants.

Grinding, however, is only half the picture when it comes to Bruxism. This research only applies to those who actively grind their teeth; it is not intended to detect teeth clenching. Additional sensors would likely be necessary to identify clenching—it is a stationary activity and therefore has little to no acceleration to detect. Experimentation in the detection of clenching would help mitigate jaw pain and tooth damage.

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