# To brux or not to brux: the development of two novel, non-invasive devices for the detection of bruxism

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## Abstract

Bruxism is a disorder in which a patient excessively grinds or clenches their teeth. Symptoms include tooth wear, headaches, back pain, and neck pain. The most common method of treating bruxism is through the use of a mouthguard. The mouthguard does not cure bruxism but only prevents the symptom of tooth wear. For this reason, researchers have attempted to reduce bruxism through biofeedback systems. Current bruxism biofeedback devices such as intra-oral pressure sensors and EMG-based systems are intrusive to wear. This study proposes two separate, novel devices that detect bruxism in a less-intrusive manner. The first device is EEG-based and collects data from the F7 electrode located above the left ear. The device uses a machine-learning discriminant-analysis algorithm to detect bruxism from the EEG data. The second device uses Eulerian Video Magnification to amplify temporal color changes in the masseter muscle as seen in a video recording (or live video feed) of bruxism. Both techniques appear to be novel approaches for the detection of bruxism. Both devices were compared to a commercial bruxism detection device to gauge effectiveness and obtain qualitative user feedback. Both of the proposed devices demonstrated statistically significant improved efficacy while being less intrusive when compared to the commercially available device.

## Review of Literature

Bruxism is the act of excessively grinding teeth and/or clenching the jaw. Bruxism may occur during the day (awake bruxism) or while the patient is asleep (sleep bruxism) [1]. Around 20% of the adult population has awake bruxism, and 8-16% of the adult population is estimated to have sleep bruxism [2]. Of these percentages it is estimated that only 20-30% have been diagnosed [3]. There are many documented causes of bruxism [4][8][9][10][11][12][13]. The current standard treatment for bruxism is a mouth guard [5]. However, a mouth guard does not actually cure bruxism; it only prevents the symptom of tooth wear [6]. Both the masseter and temporalis muscles contract when bruxing. These muscles exert force on the surrounding tissue when a patient bruxes, leading to headaches, neck pain, and back pain. Around 80% of all bruxism episodes are silent [7], making it difficult to detect bruxism without an intraoral device. In this paper I present two improved methods that I developed independently for detecting bruxism: EEG-based detection and Eulerian Video Magnification detection.

### Bruxism Symptoms

Bruxism symptoms can be separated into three groups: tooth, joint, or muscle related issues [5]. Tooth symptoms include excessive wear and frequent fractures of dental restorations. Joint symptoms involve temporomandibular disorders (TMD), and muscle symptoms involve pain in back and neck muscle groups, and in the temporalis muscle. The majority of patients that report back and neck pain go to a physical therapist before any teeth wear is apparent [6]. It is difficult for the physical therapist to make a diagnosis for bruxism because most of their patients are either unaware that they clench, or they have sleep bruxism. Similarly, a dentist has difficulty diagnosing a patient with bruxism efficiently because the dentist must first rule out other issues, such as improper mouth fillings, which may cause similar symptoms.

**Current Bruxism Treatments**

After a patient has been diagnosed with bruxism, the condition remains difficult to treat effectively. The usage of a mouth guard is sacrificial; patients wear down the plastic guard instead of their teeth [5]. Mouth guards prevent teeth related symptoms effectively but do not help the muscle and/or joint related symptoms. Furthermore, the mouth guard does not cure bruxism. For this last reason, researchers have attempted to create biofeedback systems to cure bruxism. One study treated sleep bruxism with biofeedback by waking the subject up every time he or she bruxed [13]. Although this lowered the occurrence of bruxism, the user faced considerable sleep deprivation [14]. Alternatively, biofeedback has been used to treat awake bruxism. One method for creating biofeedback systems is through the use of intraoral devices such as the intra-splint force detector, which detects the jaw force exerted on a splint [13]. This device claims a 50% success rate but was shown to fail due to the long-term exposure of the static forces normally exerted between the teeth. Another proposed device releases a taste stimulus when a user bruxes [15]. Both of these devices are intrusive for the user because they have to be placed inside of the mouth.

**Current Bruxism Detection**

Researchers have attempted to detect bruxism using EMG-based devices [16]. EMG-based devices use electrodes placed directly on one of the jaw muscles. Most products based on this technology, including Bite Strip™ (Figure 1), are placed on the masseter muscle. When the masseter contracts, an electrical potential is detectable using an electrode. The problems with EMG-based systems are: a) they require the electrodes to be placed directly on the jaw muscles;

b) they are, therefore, conspicuous to wear; c) the muscle is already contracted by the time it is possible to obtain an electrical signal; and d) they must have low sensitivity to reduce false positives during normal jaw muscle activity, making them useful only for heavy bruxers.

**Figure 1. A picture of the Bite Strip™ device. From www.greatlakesortho.com**

**Proposed EEG-based system.** Different from EMG-based devices, commercial EEG systems are designed to detect a variety of stimuli using algorithms that identify spatial and temporal patterns in neural firing [17]. An EEG-based system allows for the electrodes to be placed on the head rather than the muscle, making it possible for a less intrusive device. Typically, the spatial algorithms treat the brain holistically, combining data from all of the electrodes to predict a stimulus [18][19][20]. One method suggested for reducing the number of electrodes required to detect any particular stimulus (and therefore reducing the complexity of the data processing) is to use Independent Component Analysis (ICA) [21]. ICA is a technique that uses cross correlations between electrode data to determine which electrodes most directly contribute to registering that particular stimulus. Once a selective subset of electrodes is chosen, only EEG data from those electrodes is used to predict that stimulus.

**Proposed Eulerian Video Magnification-based system.** Eulerian Video Magnification (EVM) analyzes temporal variations (of motion or color) in video. The use of EVM for bruxism detection has never been explored. Magnifying the temporal variations allows the naked eye to see otherwise invisible changes in the video. The algorithm first applies a spatial filter to each frame in the video. Depending on the application, various spatial frequencies are then filtered out of each frame. This process has the effect of removing edges and other details that are not important. Next a temporal filter is applied to the series of spatially filtered frames. This process extracts certain movements or color changes in the desired frequency range of the video. The EVM algorithm then magnifies the motion or color in the temporally filtered frames by multiplying the individual pixel values of the temporally filtered image by an arbitrary alpha value and adds the resulting image to the original video image. The final result is a video in which the color or motion of interest is enhanced to be visible by the naked eye. Using only a video camera, EVM has successfully been used to: detect a subject's pulse [22]; detect a sleeping baby's breathing [23]; enhance vibrations of buildings and structures [24]; and reconstruct the sound vibrations of people talking by viewing a nearby bag of potato chips [24].

In this paper I present two applications that I personally created. I present both EEG and EVM-based applications as less intrusive methods for detecting bruxism. The use of a single electrode EEG-based device was explored as a method for bruxism detection because it would be less intrusive than an EMG-based device. I also created an EVM-based bruxism detection device because the user would not have to wear any device at all.  The ability to detect bruxism allows for both a bruxism diagnosis and a treatment device.

## Hypothesis

$H_1$: Bruxism can be detected using an EEG-based device with only one electrode.

$H_2$: Bruxism can be detected using Eulerian Video Magnification.

## Objectives

1. To create a less-intrusive EEG-based device with only one electrode that detects bruxism in a manner that demonstrates equivalent or improved accuracy to commercially available products.
2. To create a real-time implementation of Eulerian video magnification that detects bruxism in a less-intrusive manner and demonstrates equivalent or improved accuracy over commercially available products.

## Methods

I met with a local physical therapist who voiced his concerns about the status of bruxism detection and treatment. Researching the current bruxism literature, I confirmed his observations— there exists a substantial need for a non-intrusive method for detecting bruxism. After researching the literature on EEG-based devices, I first sought to create and implement a device that would be able to detect the onset of bruxism using EEG data. Because the EEG detects the electrical activity in the brain, a properly designed EEG device has the potential to detect the onset of bruxism before the subject actually tightens the jaw muscles.

I completed my study with little outside assistance. My mentor, John Granata (Data Scientist, at 21, Inc.), provided suggestions and general guidance for the direction of the project. I collected all of the EEG data independently. I determined how to properly configure a wireless portable EEG headset. I designed and created a custom data collection process. I programmed a microcontroller to communicate through a serial port. I wrote the MATLAB scripts and custom C++ software. I had previous knowledge with C++, however I taught myself MATLAB. I wrote and implemented the preprocessing and filtering of the EEG data. I independently researched and implemented the machine learning algorithms. I implemented a novel application using EVM to process a video signal and created an algorithm to extract bruxism information from the video. I experimented with existing EVM software available on the web. I found that it was not useful for extracting bruxism information from the video. Additionally, the EVM software available on the web was not able to run in real-time, making it of limited use for this particular application. Therefore, I had to rewrite the EVM algorithm in C++ and modify it to identify movement of the masseter muscle in real-time. Next, I had to write software to extract the bruxism motion information from the processed video and to visually alert when the subject bruxes. While implementing EVM I taught myself OpenCV, a C++ video processing library. I obtained IRB approval from my school. Lastly, I designed the final experiment and collected the data independently.

**Preliminary Data-Acquisition**

I surveyed various computer languages to determine the best approach for processing and analyzing EEG data. MATLAB was selected because it is able to load and parse large EEG datasets. The Emotiv EEG EPOC headset was used to collect all of the EEG data for this study. The Emotiv EEG headset is a wireless Bluetooth device that collects and sends EEG data to a computer with a sampling frequency of 128 Hz. The Emotiv Test Bench Software was used to create CSV files that contained the EEG data from each of the electrodes. Initially an open source tool for MATLAB called EEGLAB was used to visualize the data and verify the CSV files. My requirements exceeded the capabilities of EEGLAB, and I had to create my own data processing scripts in order to implement a classifier that detected bruxism.

A "classifier" in the machine learning literature refers to an algorithm that categorizes data based upon a set of features extracted from the data. For example, my categories are "bruxing" and "not bruxing". First, certain features need to be extracted from the data. Next, a classifier needs to be trained on actual data to distinguish between the categories. In order to train the classifier, a system is required to indicate to the test subject when to brux or when to relax while simultaneously collecting EEG data from the subject. Because no such system existed, a custom hardware data collection setup specific to this problem was designed and built. The setup (Figure 2) consists of: a) an Emotiv EEG headset that collects data and wirelessly sends it to a laptop; b) an Arduino Uno microcontroller connected to a series of LEDs that illuminate to act as a stimulus to the test subjects; c) Arduino simultaneously sends a marker over a serial connection to the data file, indicating the applied stimulus; and d) the Emotiv Test Bench Software on the laptop that streams the EEG data to a file.

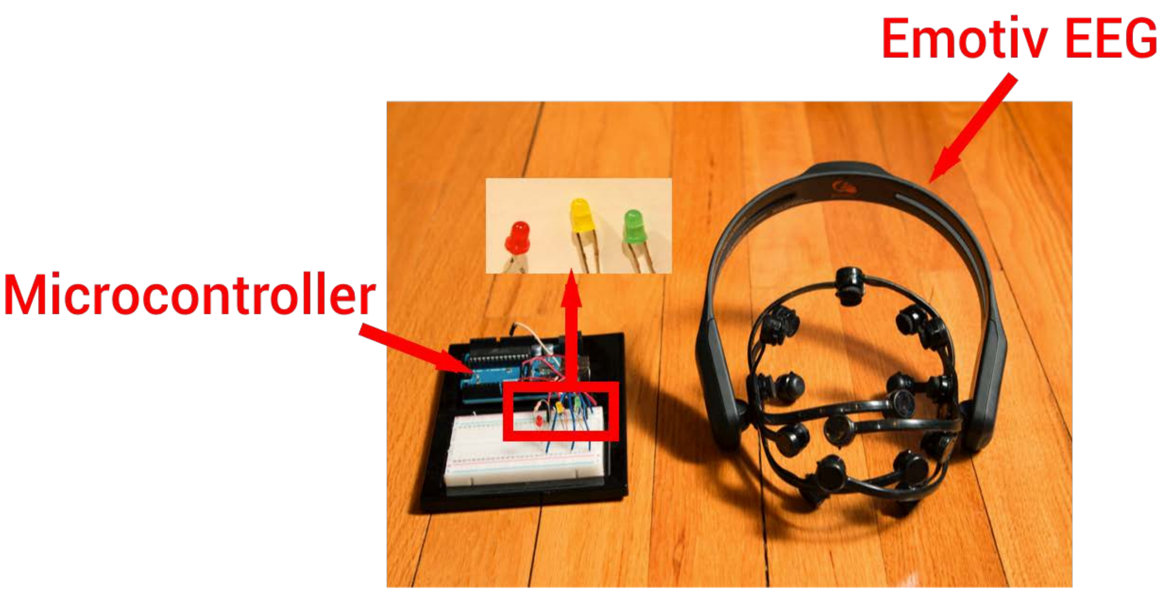


**Figure 2. The hardware used for EEG data collection. (Photo by author)**

The Arduino board is configured with one green, one yellow, and one red LED indicator. First either a green or yellow LED turns on. In order to prevent the subject from being able to predict when the stimulus indicating “clench” would arrive, the timing between LED illuminations is selected using a random number generator. The green LED signals the subject to clench while the Yellow LED signaled the user to not clench. The subject continued the given task until they observe a red LED stimulus. After a five second break period the entire process is restarted. While conducting the test: a) clench times are programmed to last a random duration between five and eight seconds; b) rest periods are programmed to last a random duration between five and eight seconds; and c) this process is repeated until data is collected for 20 clenches. Multiple datasets were collected and used to train and debug a classification system which was used to process the EEG data to identify the onset of bruxism.

**Reducing the Total Number of Required Electrodes**

To reduce the total number of required electrodes, it is necessary to determine mathematically which electrodes are the most important for detecting bruxism. These electrodes pickup the data that is most relevant for discriminating between clench and no clench.  For this reason, an Independent Component Analysis (ICA) algorithm is used on the EEG bruxism data obtained from a subject. The ICA algorithm cross-correlates the EEG-data from all of the electrodes. Next, the ICA algorithm reduces the electrical noise in each electrode created by other areas of the brain. The resulting signals demonstrates which electrode’s signal contributes most to the measured EEG response. It was found that the data from electrode F7, shown in figure 3, was the most correlated with the EEG response during bruxing.

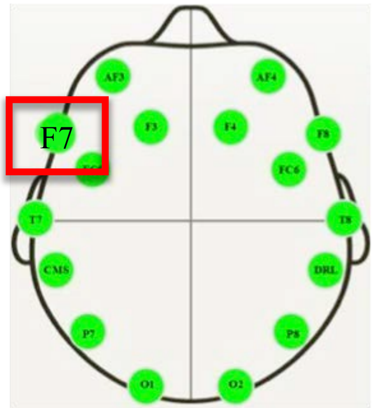


**Figure 3. An electrode map that shows the location of the F7 electrode on an Emotiv EEG, retrieved from: https://emotiv.com**

## Classifier Implementation

Using MATLAB, I created a unique classifier to process data and group it into categories statistically. I chose to use a modified linear discriminant analysis function as a classifier. The first step is to train the classifier using data collected from a subject for which the bruxism results are known. The training algorithm takes the raw EEG data and identifies important features in the stimulus for classifying bruxism. As shown in figure 4, the general procedure for creating the classification was 1) import the EEG data files and manually select the electrode to be analyzed; 2) use software to preprocess and apply filters; 3) create a function using a combination of the best bruxism-discriminating data features from the EEG datasets; and 4) test the final classification by processing EEG data in real-time.

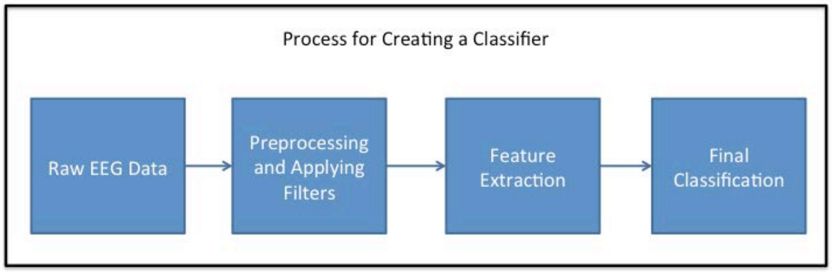


**Figure 4. The process for creating a classifier (Photo by author)**

The MATLAB script first loads the EEG data from CSV files. Each column in the CSV file represents the data from a single electrode; the final column contains the markers indicating whether or not a visual stimulus was present. The markers were written to the data file by the microcontroller based upon the presented stimulus (a green or yellow light). Although the Emotiv EEG has 14 electrodes, I used only data from the F7 electrode for the classification. A single electrode device could be easily manufactured and used as a noninvasive biofeedback device to cure or reduce bruxism. So I only considered classifiers based on one electrode.

Preprocessing the EEG data organizes the datasets for the classification by extracting specific portions of the data where the stimuli occurred. The MATLAB script first locates all of the markers and selects the EEG data from the chosen electrode surrounding each marker. A specific marker value signifies when the subject clenched, and another value signifies when the subject did not clench. The MATLAB script separates each of the datasets into two classes: positive (clench) and negative (no clench). In order to avoid over-fitting the data, the script randomly selects half of the datasets in each group for training the classifier and the other half of the datasets are used to test the final classification. After preprocessing the data, the script applies basic noise filters to the EEG data. The first filter applies a five-point moving-average filter. This filter smooths the data by averaging each point with the four previous values. Next, the data is normalized by applying a mean offset.

The data collected from the Emotiv is the electrical brain activity in the time domain. The new classifier converts this data into the frequency domain using a Fast Fourier Transform (FFT) algorithm. There are six bands of electrical frequencies generally associated with brain activity: delta (0-4Hz), theta (4-7Hz), alpha (7-14Hz), beta (15-30Hz), and gamma (30-100Hz). The classification takes the average magnitude of all points within each frequency range to create a bin and sends that information to the classifier.

The best performing classifier is a modified step-wise discriminant analysis algorithm. Using the first half of the collected data, each of the frequency points in group 1 (the clench group) and each of the frequency points in group two (the no clench group) are aligned and used to train the classifier. The resulting classifier is a multidimensional function. The function uses a set of frequency points, and returns a number between zero and one. A zero means it is definitely in the no clench classification, while a one means it's definitely in the clench classification. A threshold between zero and one is chosen to group each data set into a particular classification. A threshold of 0.5 was chosen, however, the sensitivity of the classification can be tuned by adjusting this number. Once the training is complete, the classifier is tested by applying it to the second half of the collected data.

Initially the algorithm only uses one feature (the magnitude of a single frequency component) for the classifier. The software tries each frequency component, creates an individual classifier, tests each classifier against the second half of the data, and grades all the classifiers based on how well each performed. Based on the grade received, the point that predicts the most number of clenches correctly is chosen as the first feature. The classification then repeats this same process using the previously selected feature in combination with every other frequency band. If adding any new points frequency bands show an improvement in predications it adds that band to the selected features and repeats the process. If there is no improvement in the prediction, the classification is finalized and the set of features is stored in the classification.

**Initial Testing of the classification**

The first step for testing my classifier design was to create a custom offline classifier for an initial test subject. During the session, the subject consciously clenched her teeth using the data collection process described above. A video camera recorded the session. The subject clenched 20 times, and did not clench 20 times, in each dataset. The subject informed me that she tended to clench her teeth while playing solitaire. For this reason, the subject was asked to play solitaire on a smartphone for 10 minutes while further EEG data was collected. The solitaire EEG data was then processed with the classifier in an attempt to determine whether the subject bruxed during the trial. The classification results were positive for three sections of the solitaire data. While reviewing the video recording it was difficult to determine when the subject was clenching or not clenching, even during the conscious clenching dataset. Therefore, independent verification of the solitaire data was not possible. Based on this initial testing, the test procedure was improved and used in the results section.

**Eulerian Video Magnification Implementation**

Reviewing the initial video footage from the EEG testing revealed subtle, barely-noticeable movement in the masseter muscle during bruxing. Based on this observation I decided to see whether there would be a way to process that video data to enhance this motion. I decided to use EVM to create a noncontact, noninvasive method of detecting bruxism.

A real-time implementation of the EVM algorithm was not available on the web or from Freeman [23], one of the inventors of EVM. Therefore, I created a modified implementation of EVM in C++ for real-time use specific to the bruxism detection application.

As shown in figure 5, the algorithm is applied to each frame in the video. First, a Gaussian spatial filter is applied. The spatial filter blurs and downsizes the image to a 20x20 pixel square. After down-sampling the image, the algorithm applies two Infinite Impulse Response (IIR) temporal filters. The first IIR temporal filter is a lowpass, cutting off specified low frequencies that are not of interest; the second is a highpass filter which cuts off specified high frequencies that are also not of interest. The low frequency result is subtracted from the high frequency result to obtain information about mandible/masseter muscle motion during bruxism. The difference is multiplied by an alpha factor (the magnification level). Lastly, the filter is resized to the original image and added to each colored pixel in the original frame. Essentially, the filter is a level of darkness added to each pixel in response to motion in the frequency band chosen to detect bruxism. Pixels showing mandible/masseter muscle motion become black, and other pixels remain their original color.

1. Original Image

2. Spatial Filter

3. Temporal Filter

4. Final Image

Fig. 5. Each step of EVM being applied to a bruxism image. The final image shows mandible motion inside the red square. The darkened area represents motion in the selected frequency band. (Photo by author)

To determine whether the subject is bruxing, the pixel coordinates of a rectangle are manually set to the jaw area around the masseter muscle (Figure 6). This area shows the most movement when a user bruxes. The algorithm calculates the average pixel intensity in this rectangle. When the subject is clenching, the average pixel density falls below a set threshold. Both the threshold and alpha (magnification level) determine the final sensitivity of the algorithm.

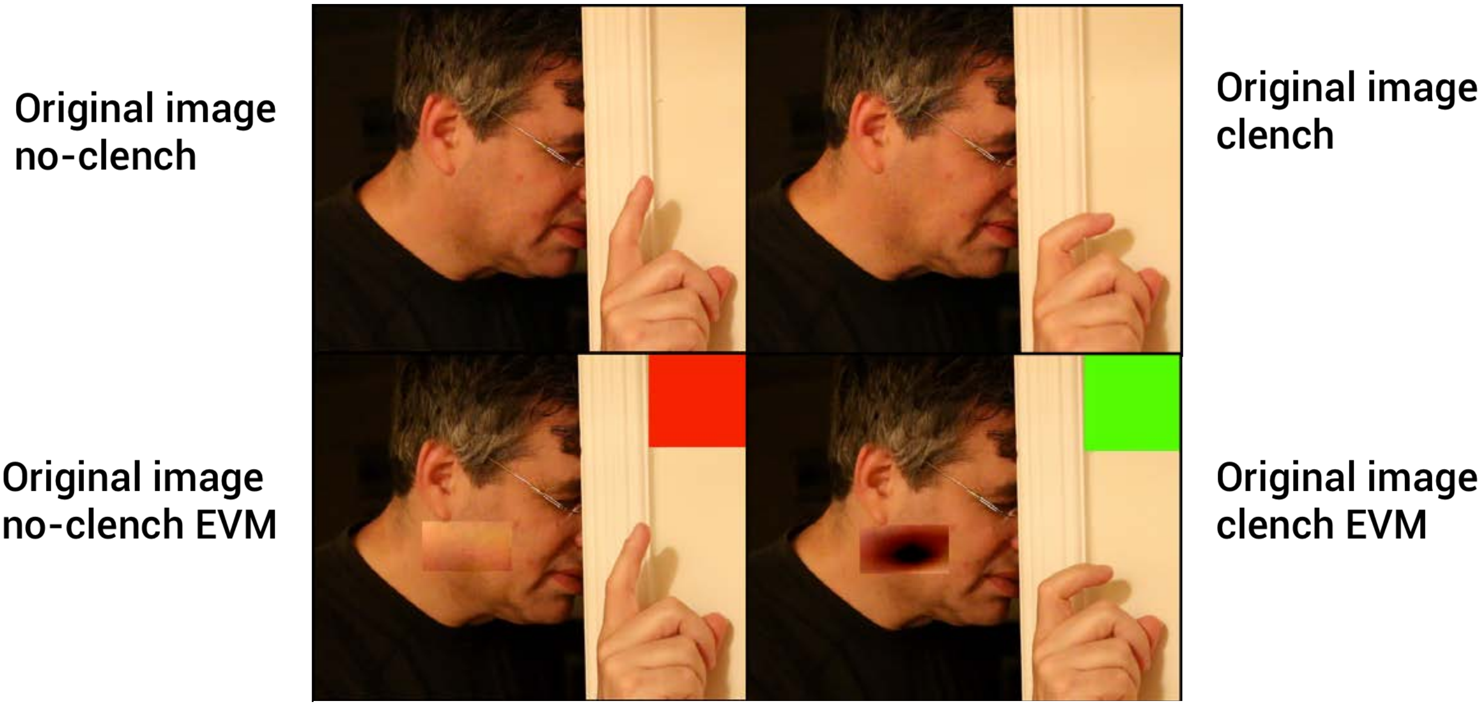


Figure 6. A comparison of bruxism detection between the original image and the images with EVM applied to the area around the masseter muscle. Note that the subject indicted clenching by lowering his index finger. The red and green indicators are automatically applied to the video image by my software based on the darkened areas in the EVM region. The head is manually stabilized to avoid having to use facial tracking (part of a future upgrade). (Photo by author)

**Testing the Detection Techniques**

The goal of testing was to show equal or improved efficacy for my novel bruxism detection implementations. The EEG classification and Eulerian Video Magnification classification were each compared to Bite Strip™. The Bite Strip™ is placed on the masseter muscle and an LED flashes when it believes the subject is clenching. There were three subjects for my study. Subject A and B were both male; subject C was female. Although none of the subjects had been previously diagnosed with bruxism, the devices analyzed activation of jaw muscle movement (clenching) which is essentially bruxism. For each device the subjects were first given a tooth protector (i.e, a Popsicle stick) on which to bite to protect their teeth. An audio recording told them to clench and release their teeth 25 times. The device's output was then recorded on a spreadsheet. The subjects then repeated the process without having a tooth protector on which to bite. The tooth protector induced each subject to bite harder (simulating heavy bruxism) while protecting their teeth. Without the tooth protector, subjects were not able to bite as hard, simulating only medium to light bruxism.

## Results

Table 1.
*A table comparing the number of clenches each bruxism detection device was able to correctly predict.*

| Subject | Bite Strip™ | | EEG | | EVM | |
|---|---|---|---|---|---|---|
| | Tooth protector | No Tooth protector | Tooth protector | No Tooth protector | Tooth protector | No Tooth protector |
| A | 23/25 (92%) | 3/25 (12%) | 24/25 (96%) | 23/25 (92%) | 25/25 (100%) | 25/25 (100%) |
| B | 24/25 (96%) | 2/25 (8%) | 24/25 (96%) | 23/25 (92%) | 21/25 (84%) | 22/25 (88%) |
| C | 25/25 (100%) | 3/25 (8%) | 25/25 (100%) | 22/25 (88%) | 23/25 (92%) | 23/25 (92%) |
| Average | 96% | 9.3% | 97.3% | 90.6% | 92% | 93.3% |

Table 1 shows the performance results from each of the devices. The Bite Strip™ performed well for heavy bruxism (96% accuracy) but it was less reliable when subjects clenched without a tooth protector in their mouth (9.3% accuracy). The EEG-based bruxism detection algorithm performed well for all subjects with or without the tooth protector (97.3% and  90.6% accuracy respectively). The EVM algorithm performed well for the all subjects with or without the tooth protector (92% and 93.3% accuracy respectively).

Table 2.
*A table comparing the efficacy of each device. The p-values were generated through a two proportion z-test.*

| | Bite Strip™ vs. EEG | Bite Strip™ vs. EVM |
|---|---|---|
| Tooth Protector | $p = .65$ | $p = .3$ |
| No Tooth Protector | $p = 4.26$ E-24 | $p = 7.7$ E-25 |

As shown in Table 2, using a two proportion z-test, there is no statistically significant difference between the Bite Strip™ detection rate and the EEG detection rate for clenches with the tooth protector (p=.65). Similarly, there is no statistically significant difference between the Bite Strip™ detection rate and the EVM detection rate for clenches with the tooth protector (p=.30). For the clenches without the tooth protector, there is a statically significant difference between Bite Strip™ detection rate and EEG detection rate (p=4.26 E-24). For the clenches without the tooth protector, there is a statically significant difference between Bite Strip™ and EVM (p=7.7 E-25).

## Discussion

### Data Interpretation

On average, all three devices statistically had nearly identical accuracy while the subject used the tooth protector. The Bite Strip™ device had poor accuracy when the user did not bite on the tooth protector. Subjects indicated that when using the tooth protector, they were able to clench much more firmly. The Bite Strip™ device is apparently accurate for only heavy clenches. Both the EEG-based classifier and the EVM algorithm performed better then the Bites Strip for softer clenches. Light to medium bruxism is more prevalent and harder to diagnose because tooth wear is less severe. I reject the null hypothesis in favor of both the first and second hypotheses. A total of 150 clenches were collected. That yields an 8% margin of error when using a 95% confidence interval. For the EEG-based classifier to be less sensitive, it could be trained to ignore moderate clenching or the classifier threshold could be lowered. A change in the sensitivity for the EVM-based technique requires only a change in one or both of a) the alpha magnification value; and/or b) the detection threshold that was applied.

## Conclusion

Both study objectives were fully met. I created and tested two separate *novel* devices for bruxism detection that use less intrusive methods than current commercially available devices, while maintaining comparable or better accuracy. I demonstrated that an EEG-based device using only one electrode can be successfully implemented to detect bruxism. Similarly, a modified EVM approach proved successful in detecting bruxism solely from video imaging. The ability to detect bruxism by remote video is *heretofore unreported in the literature,* and preliminary patent approval for the EVM approach is underway.

Because the EVM-based detection showed comparable accuracy while also being less intrusive for the subject, I will next add real-time facial tracking and stabilization to the EVM-based approach. I will then create a computer application that will use EVM-based detection with the built-in web camera common to most laptops, tablets and smartphones to create a highly portable biofeedback system that will help diagnose and/or treat bruxism.

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## References

1. Shetty. , Pitti, , Babu, C. L., Kumar, G. P., & Deepthi, B. C. (2010). Bruxism: A literature review. *J Indian Prosthodont Society*, *10*(3), 141-148. doi: 10.1007/s13191-011-0041-5

2. Glaros AG. Incidence of diurnal and nocturnal bruxism. J Prosthet Dent. 1981;45:545–549. doi: 10.1016/0022-3913(81)90044-5.

3. Peña-Cortés, César Augusto, Gualdrón, Óscar Eduardo, & Moreno-Contreras, Gonzalo Guillermo. (2014). Warning and Rehabilitation System Using Brain Computer Interface (BCI) in Cases of Bruxism. *Ingeniería y Universidad*, *18*(1), 177-193. Retrieved December 28, 2014

4. Rao, S. K., Bhat, M., & David, J. (2011). Work, stress, and diurnal bruxism: A pilot study among information technology professionals in bangalore city, india. *International Journal of Dentistry*, *2011*, 5. doi: 10.1155/2011/650489

5. Dr. Steven Brisman, Prosthodontic Dentist

6. Neil Churnick, physical thereapist, Westchester County NY

7. G. J. Lavigne, S. Khoury, S. Abe, T. Yamaguchi, and K. Raphael, "Bruxism physiology and pathology: an overview for clinicians," Journal of Oral Rehabilitation, vol. 35, no. 7, pp. 476–494, 2008.

8. Macaluso GM, et al. Sleep bruxism is an disorder related to periodic arousals of sleep. J Dent Res. 1998;77:565. doi: 10.1177/00220345980770040901.

9. Lobbezoo F, Lavinge GJ, Tanguay R, Montplaier JY. The effect of the catecholamine precursor l-dopa on sleep bruxism: a controlled clinical trial. Mov Disord. 1997;12:73. doi: 10.1002/mds.870120113.

10. Selms MKA, Lobbezoo F, Wicks DJ, Hamburger HL, Naeije M. Craniomandibular pain, oral parafunctions, and psychological stress in a longitudinal case study. J Oral Rehabil. 2004;31:738–745. doi: 10.1111/j.1365-2842.2004.01313

11. Molina OF, dos Santos J., Jr Hostility in TMD/bruxism patients and controls: a clinical comparison study and preliminary results. Cranio. 2002;20:282–288.

12. Manfredini D, Landi N, Tognini F, Montagnani G, Bosco M. Occlusal features are not a reliable predictor of bruxism. Minerva Stomatol. 2004;53:231–239

13. Takeuchi H, Ikeda T, Clark GT, J Prosthet Dent A piezoelectric film-based intrasplint detection method for bruxism. 2001 Aug; 86(2):195-202.

14. Roehrs T, Carskadon MA, Dement WC, Roth T. Daytime sleepiness and alertness. In: Kryger M, Roth T, Dement WC, editors. Principles and practice of sleep medicine. Philadelphia: Elsevier Saunders; 2005. pp. 39–50.

15. Nissani M. Can taste aversion prevent bruxism? Appl Psychophysiol Biofeedback. 2000;25:43–54. doi: 10.1023/A:1009585422533.

16. Minakuchi H, Clark GT (2004) The sensitivity and specificity of miniature bruxism detection device. J Dent Res 83(special issue A)

17. Farwell LA, Donchin E. Talking off the top of your head: Toward a mental prosthesis utilizing event-related brain potentials. Electroenceph clin Neurophysiol 1988; 70: 510-23.

18. Tanaka, K., Matsunaga, K., & Wang, H. O. (2005). Electroencephalogram-based control of an electric wheelchair. *Robotics, IEEE Transactions on*, *21*(4), 762-766.

19. Pellouchoud, E., Smith, M. E., McEvoy, L., & Gevins, A. (1999). Mental Effort-Related EEG Modulation During Video-Game Play: Comparison Between Juvenile Subjects with Epilepsy and Normal Control Subjects. *Epilepsia*, *40*(s4), 38-43.

20. McFarland, D. J., Krusienski, D. J., Sarnacki, W. A., & Wolpaw, J. R. (2008). Emulation of computer mouse control with a noninvasive brain–computer interface. *Journal of neural engineering*, *5*(2), 101.

21. Wang, Y., & Jung, T. (2013). Improving brain--computer interfaces
using independent component analysis. Springer, 67--83.

22. Balakrishnan, G., Durand, F., & Guttag, J. (2013, June). Detecting pulse from head motions in video. In *Computer Vision and Pattern Recognition (CVPR), 2013 IEEE Conference on* (pp. 3430-3437). IEEE.

23. Wu, H. Y., Rubinstein, M., Shih, E., Guttag, J. V., Durand, F., & Freeman, W. T. (2012). Eulerian video magnification for revealing subtle changes in the world. *ACM Trans. Graph.*, *31*(4), 65.

24. Wadhwa, N., Rubinstein, M., Durand, F., & Freeman, W. T. (2013). Phase-based video motion processing. *ACM Transactions on Graphics (TOG)*, *32*(4), 80.