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Use of Dry Electroencephalogram and Support Vector for Objective Pain Assessment

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Abstract

The reliability of normal gel-based electrode electroencephalogram (EEG) for measuring pain has been validated. To date, however, few documented trials have used dry EEG for pain quantification. The primary goal of this study was to objectively quantify pain using dry EEG in conjunction with a support vector machine (SVM). SVMs have been proven accurate for classifying pain intensity. The authors believe that EEG combined with an SVM could increase the statistical power of pain assessment. Currently, clinicians primarily rely on verbal (i.e., subjective) reports for assessing pain; therefore, the research described here could offer a method to objectively monitor pain, eliminate observer error, and individualize treatment.

Acute pain results directly from injury, while chronic pain is caused by an underlying disease or untreated condition and is normally treated using nonsteroidal anti-inflammatory drugs, nonopioid medications, or opioid medications.

Chronic pain conditions constitute a growing burden on individuals, employers, healthcare systems, and society in general as a result of medication complications, social losses, rehabilitation, and decreases in work productivity. In 2010, the economic burden of chronic pain was estimated to range from $560 to $635 billion, surpassing that of diabetes ($188 billion), cancer ($243 billion), and heart disease ($309 billion). Further, in 2011, chronic pain sufferers in the United States totaled approximately 100 million, outnumbering those diagnosed with diabetes (25.8 million), coronary heart disease (16.3 million), and cancer (11.9 million). In addition, untreated pain can lead to increased risk of myocardial infarction and ischemia, with other issues including loss of sleep, mobility, and strength.[1,2]

Human pain has been analyzed using various noninvasive medical imaging devices (e.g., positron emission tomography, functional magnetic resonance imaging).[2,3] Due to the high temporal resolution of electroencephalogram (EEG) devices and their ability to capture real-time, dynamic changes within the brain, researchers have concluded that they are the most suitable neuroimaging devices for pain diagnosis.[4] Therefore, the primary objective of the current study was to design an experiment that would objectively quantify pain sensation using EEG that could be used in a clinical setting. We assert that compared with normal gel-based electrode EEG, dry EEG is more feasible and allows for quicker setup time in a clinical setting.

In addition, we implemented a support vector machine (SVM) that used supervised machine learning to predict offline and real-time changes in pain stimulus levels. Frequency band power data (described below) were obtained during EEG recordings. The raw data were processed using power spectral analysis, and the results were input (i.e., features) into an SVM algorithm.

Dry versus Gel-Based Electrode EEG

The Cognionics Quick-20 dry EEG headset (Cognionics, San Diego, CA) was used in the current study. Quick-20 dry EEG (19 channels) differs from normal EEG in that it does not use gel-based electrodes. It has the advantage of quicker setup time, increased versatility, and improved mobility. It also has increased resistance against movement and electrical artifacts and can measure impedance in real time. Previous results have shown that this device has the same quality of raw data collection as that of the current gold standard (i.e., wet EEG).[5]

In terms of disadvantages when compared with wet EEG, dry EEG recordings include more impedance due to the lack of gel, which

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normally is used to fill gaps between the electrodes and the surface of the scalp. In addition, the dry system must overcome shortcomings pertaining to sensor design, mechanics, and electronics.[6]

Power Spectral Density

Variations in brain neural activity cause increases and decreases in the amplitude of EEG signals in the time domain. These variations are known as the "power" or energy of the EEG waves. In signal processing, to derive power, one must take the average of the magnitude of the signal, then square it. Spectrum refers to variations in frequency of an entire wave signal.[7]

Therefore, power spectral density can be used to characterize brain activity by tracking changes in amplitude of frequency waves. Figure 1 shows EEG time signals converted to the frequency domain. Each frequency band shown in Figure 1 is related to a specific brain function. The brain contains billions of specialized cells (called neurons) that are recruited in populations, numbering in the thousands, to perform a specific task. Neuron rate of recruitment, or "firing rate," is displayed as power fluctuations in EEG data. For example, high alpha frequency band power has been shown to be associated with processing painful stimuli.[8]

Null Hypothesis

We believe that all people experience pain differently. Therefore, our null hypothesis was that everyone's pain experience would be similar when exposed to the same modality and magnitude of pain stimuli; thus, no significant differences in EEG data would be observed.

Methods

We started with a pool of 15 subjects, but as a result of noisy data, the study sample consisted of nine participants. "Noisy data" refers to data that are convoluted with meaningless

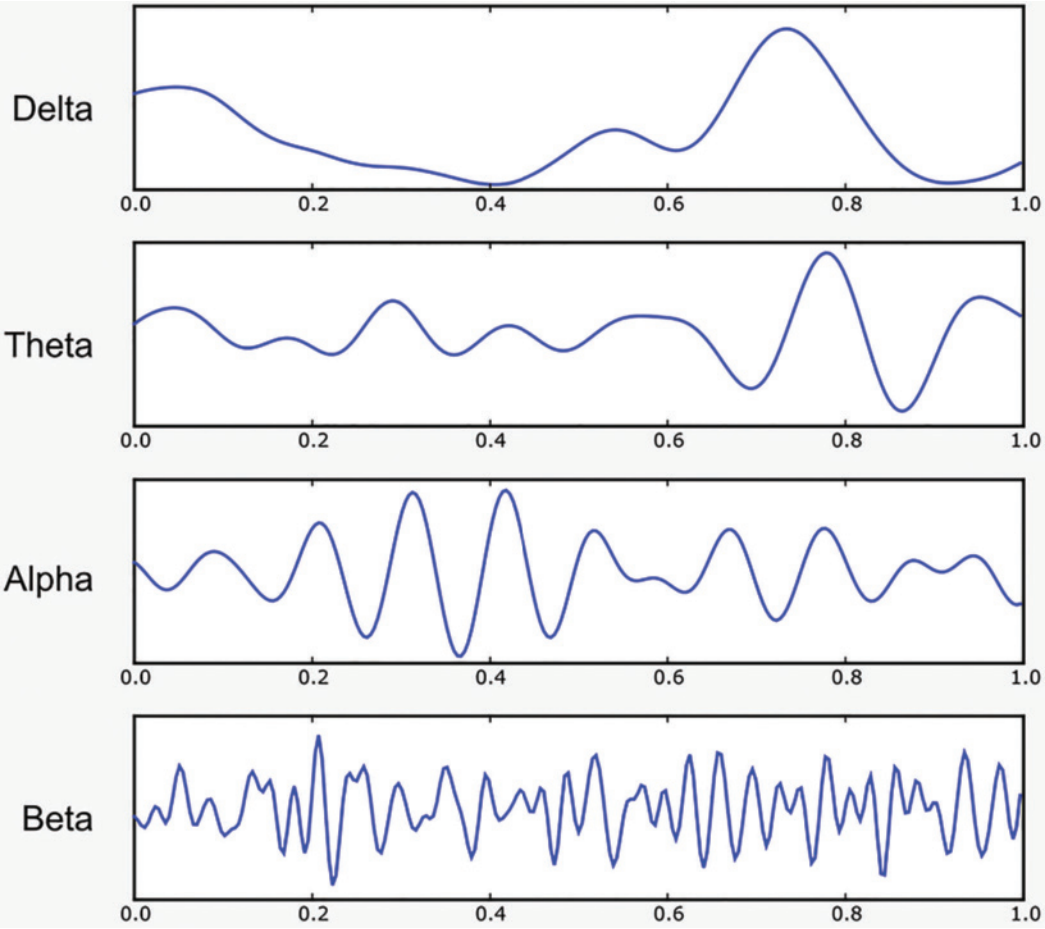

Figure 1. Example electroencephalogram waveforms in the frequency domain showing delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), and beta (12–28 Hz) frequency bands.[19]

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information, which is common during EEG recordings, because it is highly sensitive to movement (e.g., blinking, muscle twitch, motion near device). We chose seven men and two women from three age categories (20–29 years, n = 5; 30-39 years, n = 2; and ≥40 years, n = 2). As a result of the examination method, subjects were required to not have any preexisting injury in either hand. All participants were required to sign a consent form, which was approved by the institutional review board at the University of Houston, before testing began.

Subject Comfort

Participants were tested in an isolated, temperature-controlled room. They first were asked to sit comfortably in a chair with both hands placed palm down on a table. The adductor pollicis muscles of the subject's hands were marked to ensure accurate and consistent pressure stimulus application (Figure 2). A wireless, dry EEG then was connected to the subject's scalp while instructions were read. Subjects were told to hold a time-sensitive trigger throughout the test. They were instructed to press the button when 1) the initial signal (stated as "press trigger") was given, 2) discomfort was first experienced (threshold), and 3) stimulus pressure became unbearable. Subjects could opt out at any time.

Figure 2. Quick-20 dry electroencephalogram device connected to detect brain waves. The hands of study subjects were marked at the adductor pollicis muscles to indicate points of stimulus.

Experimental Procedures

Tactile stimulation was performed using a Wagner pressure gauge (Wagner Instruments, Greenwich, CT). During the baseline trial, the pressure gauge was placed on the surface of subjects' hands, but no pressure was applied. Afterwards, the tester applied pressure with the 1-cm^2 tip while monitoring the pressure of the algometer. Pressure was slowly increased during each trial at a fixed rate of 1 kg (2.20 lb) every 30 seconds to a maximum of 5.5 kg (12 lb). The results were recorded in pounds.

Measures

A one-minute interval of rest occurred between each trial to avoid pain wind-up.[9] Excluding baseline, during which no stimulus occurred, each trial consisted of 1) low stimulus (beginning of trial to threshold), 2) high stimulus (threshold to max stimulus/end of trial [i.e., tolerance]), and 3) rest (no stimulus occurring between trials). Data were separated into time epochs, then analyzed in MATLAB (MathWorks, Natick, MA) using support vectors to categorize pain.

Preprocessing

EEG-signal data were sampled at 500 Hz. Preprocessed signals were visually examined for high amounts of convoluted data and, if present, omitted from the study. Butterworth and notch filters were used initially to eliminate noisy data.

Supervised Machine Learning with SVM

Feature Extraction

The study was performed using eight frequency band powers captured in the 19 channels as features ($8 \times 19 = 152$ features): delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta1 (12–16 Hz), beta2 (16–20 Hz), beta3 (20–24 Hz), beta4 (24–28 Hz), and low gamma (28–32 Hz) bands. The label vector was supplied to the machine-learning algorithm, which included stimulus levels (no, low, and maximum stimulus). Time epochs occurring before baseline and after the end of the final trial were discarded.

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Classification

We constructed feature vectors containing frequency band powers obtained through power spectral density for 19 channels. Then, a label vector for pressure stimulus levels was created for each row (no, low, and high stimulus). Afterwards, an SVM was used to compare each individual observation.

Type of classification. Linear classification was performed using an SVM to predict a maximum margin classifier for 1) rest versus low stimulus, 2) rest versus maximum stimulus, and 3) low versus maximum stimulus.

The SVM algorithm is determined by a binomial classifier: $(c) = \sum a_i k(s_i, x) + b$, where c is used to classify observations in vector x. When $c \geq 0$, then x is classified in the first group, and when $c < 0$, x is placed in the second group. The contribution of each x vector is explained by a_i. The kernel function (k) becomes a dot product when using a linear kernel. The support vectors are represented by s_i and the bias by b.[10]

Validation

The efficacy of the SVM algorithm was assessed using the rate of true negatives (specificity), true positives (sensitivity), and correctly identified observations (accuracy). Standard error and P values were calculated for individual and group classifications using a binomial test.

Results and Discussion

Relative Band Powers

Figure 3 displays results for relative EEG band power. The height of each bar represents relative band power, taken as the mean value during the three conditions. A one-sample t test was used to determine any significant changes. Standard error bars describe the amount of variability in each result from tenfold cross validation.

The results show that relative change in each frequency band power from rest to painful states decreased significantly at the 5% level: delta ($P = 0.002$), theta ($P = 0.004$), alpha ($P = 0.005$), beta1 ($P = 0.005$), beta2 ($P = 0.009$), beta3 ($P = 0.013$), beta4 ($P = 0.015$), and low gamma ($P = 0.024$). This means that there is only a 0.05 (5%) chance of incorrectly assuming these differences in brain activity resulted from test conditions. The results indicate that neural activity decreased throughout the cortex as a result of increasing pain stimulus.

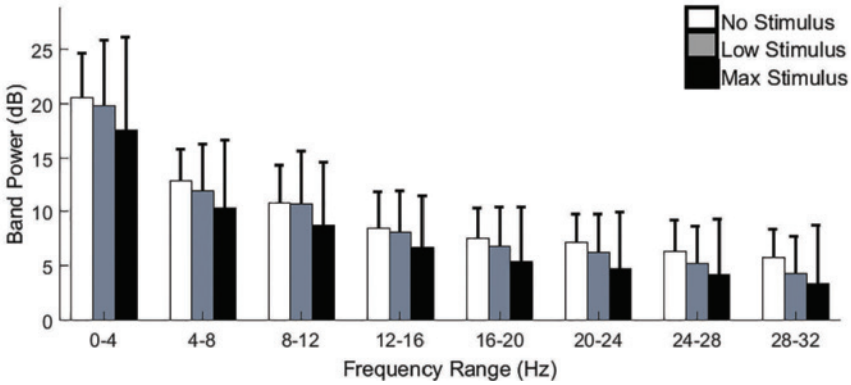

Figure 3. Relative electroencephalogram frequency band power in multiple frequency ranges for window size (6 s). The results were averaged across observations, channels, and subjects. All changes in relative band powers were significant at the 5% level.

The significance of these results, when taken in context with previous studies, is that increased pain normally leads to decreased average power density in delta, theta, alpha, and beta ranges (2–25 Hz).[9,11] Our results for delta and theta were similar to a previous study involving cold pain in which these powers were highest.[12]

Difference in Band Powers

Figure 4 shows the difference between the subjects' band power for each condition. Red, blue, and green indicate that an increase, decrease, or no change in power of frequency occurred, respectively, during changing stimulus levels.

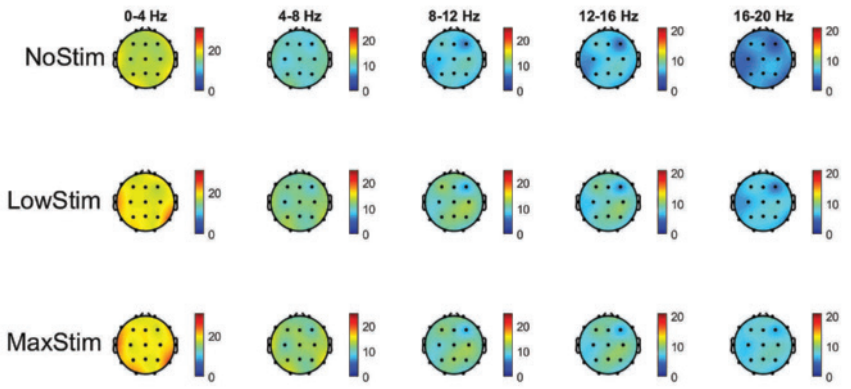

Figure 4. Topographic distribution of frequency band power. The window size was six seconds, and the results were averaged across subjects and observations. Abbreviations used: LowStim, low stimulus; MaxStim, maximum stimulus; NoStim, no stimulus.

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Changes in frequency power appeared consistent for each condition. Power was high for lower frequency bands (i.e., delta, theta), then decreased with rising frequency. These results indicate that the entire brain response to pressure pain stimulus is relatively the same.

Static changes in resting-state EEG have been reported in previous experiments dealing with pain; this does not indicate unusable data but could reflect brain activity not explicitly studied. Alpha (1–4 Hz) and theta (4–8 Hz) bands had the highest average power. Both have been shown to be highly associated with pain.[12,13]

Subject-Specific SVM Algorithm

Figure 5 displays accuracy of binomial classification using the SVM algorithm to determine moments of rest versus low stimulus, rest versus maximum stimulus, and low versus maximum stimulus for individual subjects. The height of the bars represents accuracy (expressed as a percentage). Each comparison was completed with changing window sizes of two, four, and six seconds.

We achieved accuracy near 100% during individual trials when classifying for each condition. The maximum classification accuracies were as follows: low versus maximum stimulus, 85% ± 27%; rest versus low stimulus, 98% ± 17%; and rest versus maximum stimulus accuracy, 98% ± 23%. The lowest accuracy occurred for low versus maximum stimulus (20%). Accuracy was calculated as the area under a binomial density curve. Table 1 shows mean (±SD) classification accuracy for each comparison.

Limitations

Due to our small sample size, all results should be considered theoretical and not based on concrete evidence.

Conclusion

We used SVMs to showcase frequency band changes that showed significance at the 5% level. With relative band power, we were able to show that at rest and during pain states, EEG power tends to be increased at lower frequencies, such as delta (1–4 Hz) and theta (4–8 Hz) bands. The results demonstrate that a dry, wireless, quick-20 EEG can

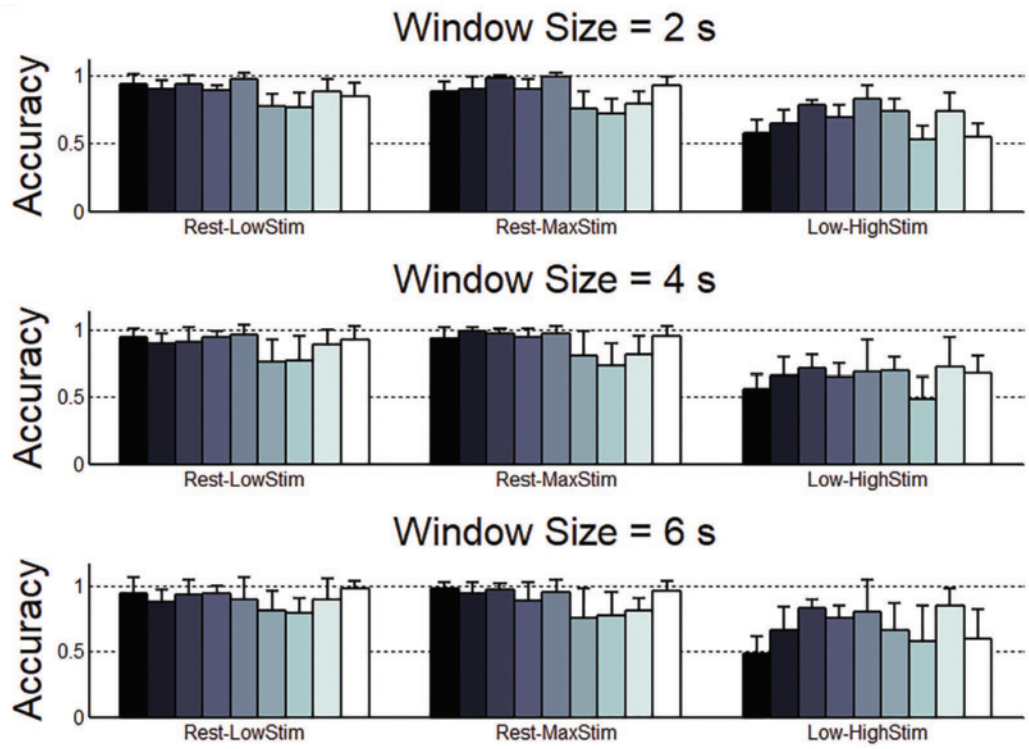

Figure 5. Accuracy of binomial classification for multiple window sizes. Subject-specific support vector machine (SVM) data are shown (i.e., SVM trained for individual subjects). Each bar represents one subject. Abbreviations used: HighStim, high stimulus; LowStim, low stimulus; MaxStim, maximum stimulus.

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Low vs. Maximum Stimulus (%) Mean ± SD	Rest vs. Low Stimulus (%) Mean ± SD	Rest vs. Maximum Stimulus (%) Mean ± SD
48.00 ± 13.27	94.33 ± 12.48	98.33 ± 5.00
66.61 ± 17.95	87.78 ± 9.70	94.67 ± 8.19
83.27 ± 6.74	93.33 ± 11.06	97.09 ± 4.79
75.28 ± 9.72	94.56 ± 5.45	89.00 ± 14.28
80.00 ± 24.49	90.00 ± 16.58	95.00 ± 10.00
66.67 ± 20.71	81.00 ± 15.78	75.50 ± 22.85
57.50 ± 27.25	79.00 ± 11.58	78.00 ± 17.46
85.50 ± 13.12	90.00 ± 15.28	81.67 ± 8.98
60.00 ± 21.91	98.00 ± 6.00	96.33 ± 7.37

Table 1. Classification accuracy for nine subjects and three binary classifications. Because we were able to use support vector machine classification to achieve accuracy near 100% for individual electroencephalogram (EEG) recordings, these data indicate that wireless, dry EEG was successful in capturing changing brain patterns resulting from rising pain stimuli.

effectively capture changes in brain activity resulting from pain.

Pain testing can be subjective. For example, in two different studies, both using the same method of pain stimulation (cold water pain), the results varied. Hadjileontiadis et al.[14] performed an investigation using varying temperatures of tonic cold pain combined with a quick-20 dry EEG to detect changing brain patterns. The authors reported observing an occurrence of no changes in frequency band power in the presence of changing stimulus intensity. In contrast, using gel-based electrode EEG, Gram et al.[12] reported significant changes occurring in all frequency band powers, such as increases in delta (1–4 Hz), beta (18–32 Hz), and gamma (32–72 Hz) bands and decreases in theta (4–8 Hz), alpha1 (8–10 Hz), and alpha2 (10–12 Hz) bands.

One cause for these differences was provided by Pinheiro et al.,[15] who reported that changes in band power depend on the type of injury and stimulus producing discomfort. For instance, theta power has been shown to increase from rest for patients enduring neuropathic pain and migraine but not among fibromyalgia patients or those with back pain. Vécsei et al.[16] noted that the majority of these studies also found that theta and alpha band changes were the most highly correlated with pain, and Pinheiro et al. suggested that increases in theta band power could serve as biomarkers in severe neuropathic pain. We saw similar changes in all frequency bands. However, due to our sample size, a larger study, perhaps with more than one pain modality, will be needed before valid conclusions can be drawn. [16–18]

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