# Objective Pain Measurement based on Physiological Signals

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*Abstract*— In an attempt to understand human physiological signals when an individual is subjected to pain, we set up a tonic pain experiment in a laboratory setting. The subjects' physiological signals were recorded, timestamped, and compared to an initial 30 second baseline measurement. Subjects were also asked to verbally state their level of pain based on a visual analog scale in order to compare reported pain levels with physiological signals. The physiological signals measured were: Electroencephalography (EEG), Pupillary Unrest Under Ambient Light (PUAL), Skin Conductance (SC), Electromyography (EMG), Respiration Rate (RR), Blood Volume Pulse (BVP), Skin Temperature (ST), Blood Pressure (BP), and Facial Expression (FE). ANOVA and frequency domain analyses were conducted on the data in order to determine whether there was a significant difference between the 'pain' and 'no pain' (baseline) states of an individual. Based on our results, skin conductance, PUAL, facial expression, and EEG signals were theorized to be good signals for the classification of tonic pain, or any pain applied directly to an individual.

Keywords - Objective Pain Measurement, Physiological Signals, Electroencephalography, Skin Conductance, Facial Expression.



## BACKGROUND

In the medical field, pain is an important factor in the treatment of patients, particularly in regard to patients in a critical state before and after surgery. Therefore, an accurate measurement of a patient's pain intensity level is an essential element for clinical care. Currently, the most common measurements for pain intensity in clinical settings are the faces rate scale, numerical rating scale (NRS, shown in **Fig. 1**), visual analog scale (VAS), and verbal rating scale (VRS). Over the past 20 years, more than 50 studies have been published comparing their use in multiple contexts using different analyses (Ferreira-Valente, Pais-Ribeiro, & Jensen, 2011; Hjermstad et al., 2011). Despite this, each study has had differing recommendations as to which scale is the most effective. Furthermore, these methods are subjective, which can lead to inconsistent data and conclusions (Chanques et al., 2010; Lund et al., 2005; Williamson & Hoggart, 2005).

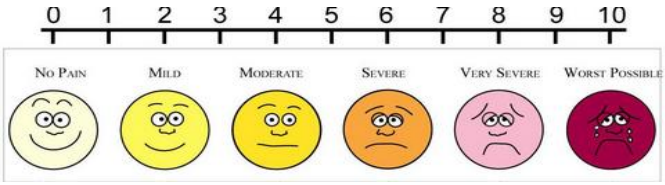


**Fig. 1.** A typical faces rating scale and numerical rating scale (NRS) used in medical institutions.

There are various pain scales and tests being utilized in the medical field such as the Brief Pain Inventory, the Checklist of Nonverbal Pain Indicators, the Critical Care Patient Observation Tool (CPOT), and the McGill Pain Questionnaire. All these tests, however, involve a medical professional examining or specifically questioning the patient on their condition (Cleland, 2005). All of the results of these tests are based on the examiner's judgement regarding the patient's situation. Thus, these scales may: (1) Not take all factors regarding the patient's situation into consideration; (2) Introduce an examiner bias that may affect the final result of the test (Jensen, 2003); and (3) Introduce a patient bias, where one patient's understanding of pain may differ from another's (Jensen, 2003). The CPOT achieved the most non-subjective pain test, however, this is also dependent on observations of patient expression and concentration (Gelinas, Fillion, Puntillo, Viens, & Fortier, 2006).

## MOTIVATION

Subjective evaluations are the pervading theme within modern pain scales and assessments. Our proposition attempts to minimize any subjective evaluations or biases introduced by assessors who are not the patient (Hsieh, Tripp, Ji, & Sullivan, 2010). The goal is to keep the factors that determine the results of the pain scale directly correlated to the patient only; in other words, keep the results of the test as objective as possible.

The primary area of concern regarding the subjectivity of pain is the way clinicians use subjective scales as a factor in determining treatment plans for patients. Patients reporting

intense feelings of pain may be administered strong pain relievers and antibiotics. While those exhibiting minimal pain may be administered a more moderate dosage (Turk et al., 2003). This creates the possibility of misdiagnosis of a patient's illness, leading to problems for both patient and clinician.

Furthermore, a patient could potentially lie to their doctor regarding their pain intensity to obtain certain pain relievers for recreational use. This is an issue that the study of substance abuse attempts to tackle by introducing screening tools. However, developing an all-in-one solution that utilizes a patient's physiological signals could minimize the need to conduct time consuming screening evaluations. It would expose patients who would lie about their conditions.

Lastly, the development of a pain assessment tool based on physiological signals would minimize the time a patient spends in triage (Krebs, Carey, & Weinberger, 2007). Since patients' vitals are also taken during this time, the vitals data could also be extracted from the assessment tool. In addition, by providing a more accurate indicator of the patient's condition, the medical staff could use it to determine the degree of urgency for patients awaiting hospital admission.

### *Objectives*

It has been suggested that the core domains that pain measures should be intensity, physical symptoms, and certain aspects and qualities (Dworkin et al., 2005; Turk et al., 2003). In order to solve the aforementioned issue regarding subjective pain testing, we propose the development and design of an objective multi-modal pain classifier. This would eliminate the need for subjective scales and potential misdiagnosis from pain measurement by using Electroencephalography (EEG), Pupillary Unrest Under Ambient Light (PUAL), and Skin Conductance (SC), Electromyography (EMG), Respiration Rate (RR), Blood Volume Pulse (BVP), Skin Temperature (ST), Blood Pressure (BP), Facial Expression (FE) (Evans, Hodgkinson, & Berry, 2001; Neice, 2017; Tejman-Yarden et al., 2016). Then, sensor fusion algorithms will be performed to classify the pain levels based on the above.

## EXPERIMENTAL PROCEDURE

This study was approved by Northeastern University IRB (IRB#: 17-01-25). Consent to partake in the experiment was obtained from all subjects involved. The Thought Technology Data Acquisition system was used to collect physiological signals. The Enobio 32-Channel was used to collect EEG data. The Tobii Glasses pro was used to collect pupil diameter data. An Omron blood pressure device was used to measure blood pressure. A built-in web camera was used to record facial expression. The experimental procedure went as follows:

1) Timestamps were collected from a screen recorder to ensure proper timestamps on trial sets.
2) Sensors were attached to the subject at their respective locations. These locations are:
   a) Skin Conductance (SC): Ring and Index finger
   b) Blood Volume Pulse (BVP): Middle finger
   c) Electromyograghy (EMG): Left forearm
   d) Respiration Rate (RR): The circumference of the subject's upper stomach.
   e) Skin Temperature (ST): The back of subject's non-donminant hand
   f) Blood Pressure (BP) : Upper arm
   g) Facial Expression (FE): In front of subject's face
   h) Electroencephalography (EEG): On subject's scalp (using 10-20 system to place the electrodes)
   i) Pupil diameter: in front of subject's eyes
3) The subject was asked to relax and a 30 second recording of all sensors was taken as a baseline measurement.
4) Simultaneously, the subject was asked to maintain focus on a green dot displayed on a monitor in front of them.
5) After 30 seconds, the subject was asked to place their dominant hand into a bucket containing water and ice. Every 30 seconds, the subjects were asked for their:
   a) Pain threshold
   b) Discomfort
   c) VAS pain experience
   d) Psychological preparedness (This included questions pertaining to whether the subject expected the sensation of pain to be as intense as it was).

## DATA ANALYSIS

### Subjective rating of pain level

During the experiment, subjects were asked to indicate their level of pain based on the VAS. This was done in order to determine whether there would be a difference in reported pain versus the response in physiological signals. It showed that there was a general increasing trend in the reported pain level of the subjects, despite no change in the temperature of the ice water or any other variables.

### Physiological Signal Analysis

After acquiring the data from the Thought Technology system. It was exported into a CSV file for review in Excel. Since time synchronization between EEG and physiological signals was not present, baseline and trial measurements were manually extracted and categorized by timestamping a screen capture video of the data.

The platform used for analysis was MATLAB. For all the physiological signals, an analysis of variance (ANOVA) was used to test the null hypothesis ($p < 0.05$) for each trial including the baseline. This will determine whether there were any significant differences between each 20 second trial and the baseline recordings. EMG, Respiration Rate, Skin Temperature, and Blood Pressure did not show significant differences.

#### *Blood Volume Pulse*

Blood Volume Pulse (BVP) device bounces infrared light against a skin surface and measures the amount of light reflected. The amount of light reflected varies with the amount of blood that is present in the skin – vasomotor activity and sympathetic arousal. The peak-to-peak amplitude of the signal will vary with respect to the changes in sympathetic arousal. BVP was used to calculate heart rate and heart rate variability (HRV). It is shown in (Faye et al., 2010) that the decrease of high frequency HRV can indicate post-operative pain. The

heart rate of one subject in painful and non-painful state is shown in **Fig. 2.**

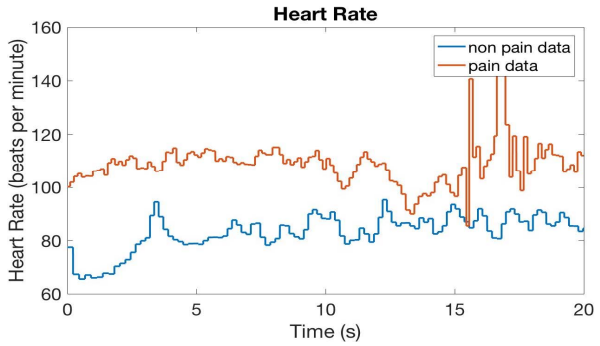


**Fig. 2**. An exemplary plot showing heart rate under pain and no pain state.

The time-domain method was used to calculate the heart rate variability. The Root Mean Square of Successive Differences (RMSSD) between each heartbeat were calculated. The HRV of each subject in non-painful and painful state was shown in **Fig. 3**.

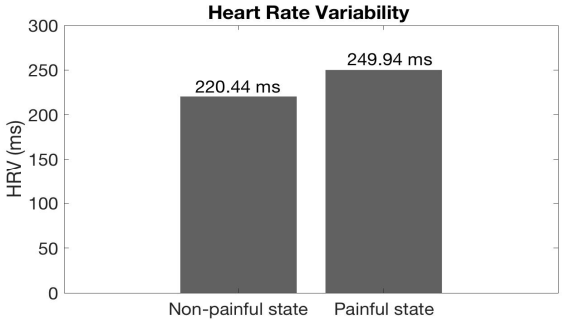


**Fig. 3**. Subjects' mean HRV in non-painful and painful state.

***Electromyography***

Electromyography (EMG) is the measurement of muscle activities by detecting and amplifying the tiny electrical impulses that are generated as the muscle fibers contract. The electromyography is the measurement used to measure the activation signal of muscles. This sensor is required to be placed on the muscle belly and its positive and negative electrodes are to be parallel to the muscle fibers. Depending on the muscles under observation, the measured EMG potentials can range between less than 50 microvolts to within 20-30 millivolts. Surface EMG was proved a useful indicator for pain assessment in (Ambroz, 2000). **Fig. 4** shows the EMG of one subject in painful and non-painful state.

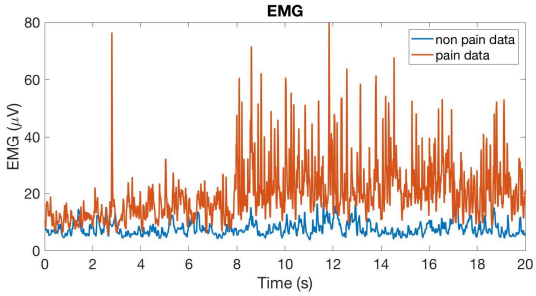


**Fig. 4.** EMG data in painful and non-painful state.

***Skin Temperature***

The body's peripheral temperature, as measured on its extremities, will vary according to the amount of blood perfusing the skin. This, in turn, is dependent on the subject's state of sympathetic arousal. A study by (Sadler, Stratton, DeBerry, & Kolber, 2013) shows that pain intensity can affect skin temperature. One subject's skin temperature is shown in **Fig 5**.

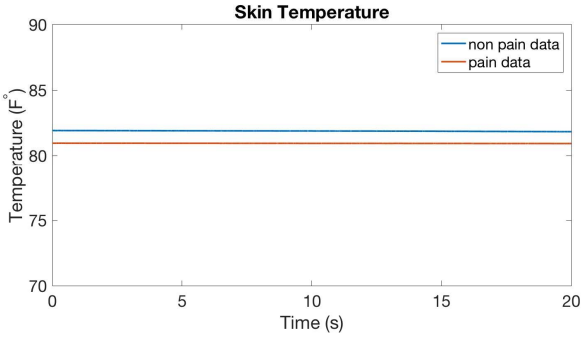


**Fig. 5.** The skin temperature of one subject in painful and non-painful state.

***Respiration Rate***

The respiration sensor is an elastic medium that is sensitive to stretch. This sensor is strapped around the subject's chest or abdomen, and converts contraction and expansion of the rib cage of abdominal region – rise and fall of the signal. Respiration rate is number of breaths that a person takes per minute. It was found to be associated with acute pain in (Stevens, Johnston, Petryshen, & Taddio, 1996). The respiration rate of one subject is shown in **Fig. 6**.

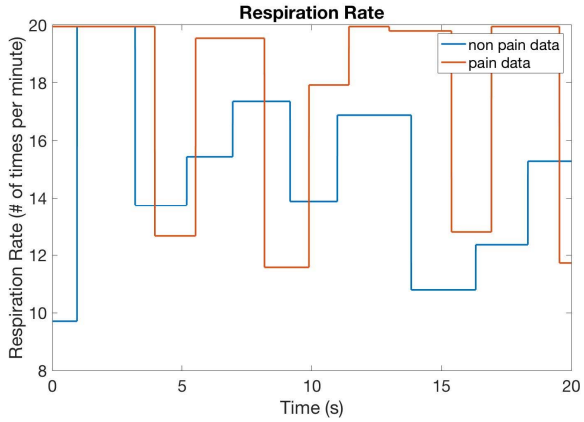


**Fig. 6**. The respiration rate of a subject in painful and non-painful state.

***Blood Pressure***

Blood pressure also plays a key role when responding to pain. Blood pressure sensors are typically non-invasive as they are designed to measure systolic, diastolic, and mean arterial pressure via the subject's oscillating blood pressure responses. One study (Fillingim & Maixner, 1996) showed higher blood pressure indicated a lower pain sensitivity. **Fig. 7** shows the blood pressure of a subject in non-painful and painful state.

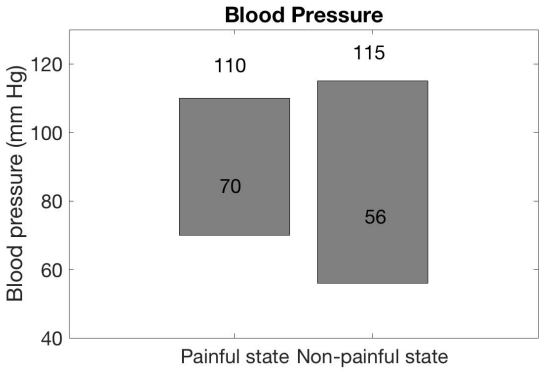


**Fig. 7**. An exemplary blood pressure in non-painful and painful state (upper: systolic pressure, lower: diastolic pressure).

***Skin Conductance***

Skin conductance is a measure of the electrical conductance of skin based on the perspiratory gland activity. In this study, skin conductance data was collected on two fingers: the ring finger and index finger. For skin conductance, the following parameters are calculated: (1) mean value; (2) standard deviation; (3) skin conductance change, which is calculated as the difference between pain state and non-pain state. Skin conductance was found to increase as the pain level increased, as shown in **Fig. 8**.

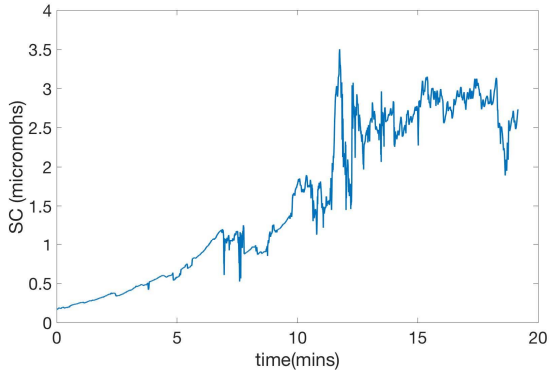


**Fig. 8.** An exemplary skin conductance plot showing skin conductance increasing as pain level increase

It was proved that fluctuations of skin conductance in unit time was related to postoperative pain (Ledowski et al., 2007). A lower fluctuations of skin conductance indicates a lower postoperative pain level. **Fig. 9** shows the number of fluctuations of skin conductance in a second in non-painful and painful states.

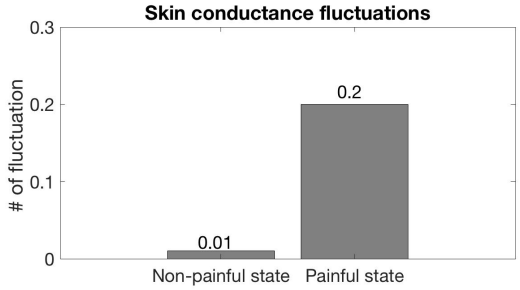


**Fig. 9**. The mean fluctuations of skin conductance of subjects in non-painful and painful states

**Pupillary Unrest Under Ambient Light**

Pupil unrest is the fluctuation of people's pupil diameter in both dark and bright environments. PUAL is calculated by computing the area under the curves (AUC) of the fast Fourier transformation of pupil diameter. It's proved in (Bokoch, 2015) that the relevant frequency range of the AUC is from 0.2 to 2.7 Hz. The fast Fourier Transformation plot of the pupil diameter is shown in **Fig. 10**.

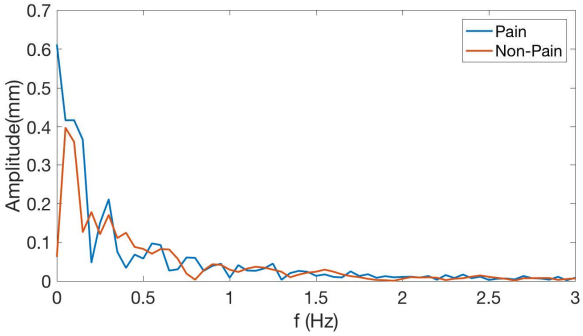


**Fig. 10**. FFT of pupil diameter plot from an exemplary subject (blue line shows the fft diagram of pain data, and orange line shows the fft diagram of non-pain data)

One-way ANOVA was performed to test the difference between the pain state and non-pain state. The mean PUAL of pain data set is 0.1345 and the mean PUAL of non-pain data set is 0.1132. The p-value of t-test is 0.014, which means the differences between two sets of data are significant at 0.05 level.

**Facial Expression**

Facial expressions analysis is used for predicting pain intensity. This method is based on a set of facial landmarks (Werner et al., 2013). For each image from a given video, we first detect the region of the face using the Haar-like feature cascade detector (Lienhart, Kuranov, & Pisarevsky, 2003). After that, an ensemble of regression trees, which is based on

**Fig. 11.** Face landmarks estimation on subjects who are under pain

gradient boosting, is applied to estimate the facial landmark positions (Kazemi & Sullivan, 2014). This algorithm is of high quality of accuracy and good real-time performance that suits our scenario. The facial landmarks extracted include: chin, left and right eyebrows, left and right eyes, nose bridge and tip, top and bottom tip. The outcome is shown in **Fig. 11**.

The images were from the Shoulder-Pain dataset (Lucey et al., 2012) which is widely used for pain intensity estimation. The features of distances were extracted to capture the facial responses during pain. The distances between the eyebrows and eyes, eyes and mouth, eyebrows and mouth, as well as the width and height of the mouth were calculated. They were compared with those extracted from the images of which the pain intensity was already known through multivariate analysis of covariance and cluster analysis to figure out the differences and similarities. The final prediction would belong to the intensity that has the most similarities. Real time testing results are shown in **Fig. 12.**

**Fig. 12.** Real time tesing results showing the pain level of a subject

**EEG Analysis**

EEG is an electrophysiological monitoring method that records the electrical activity of the brain. This paper focused on a topography analysis of brain activity in order to determine which regions of the brain were stimulated when experiencing pain. Topographies allowed us to determine whether brain activity was a viable physiological signal for the determination of the presence of pain.

In data preprocessing, we used a 2-40Hz bandpass filter, common average reference (CAR), and independent component analysis (ICA). ICA is a powerful technique and is able to separate independent sources linearly mixed in several sensors. In our experiment, we used ICA to remove eye blinking and eye-movement artifacts from the raw EEG data.

EEG signals can be divided into the following frequency band: delta (<4 Hz), theta (4-7 Hz), alpha (8-15 Hz), beta (16-31 Hz), and gamma (>32 Hz). These frequency bands were used to investigate the differences for a 'Pain' and 'No Pain' state of subjects. Frequency domain analysis for EEG signals followed a few steps. We obtained the EEG power band topography. In **Fig. 13**, the first (left) image shows the baseline data topography. The second (middle) image shows the topography for the median time of the subject. The third (right) image shows the topography at the end of the procedure. In the graph, a blue hue usually indicates a low power signal while the red hue symbolizes a powerful signal. We analyzed the EEG data in five different frequency ranges, finding that the delta frequency band was ideal for analyzing the EEG data (Chen & Rappelsberger, 1994).

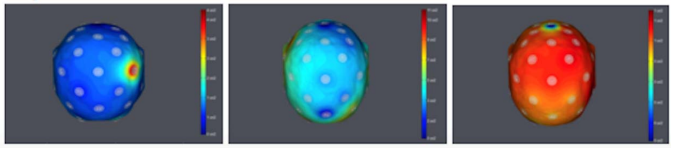

**Fig. 13**. Topographies of exemplary subject.

Four components' features from a subject are shown in **Fig. 14**. The first two components were useless, and the last two components were useful. The first two components provided no value to our analysis because they were mixed with eye artifacts, which produced noise and polluted the signal. However, we removed said artifacts using ICA to obtain the filtered data.

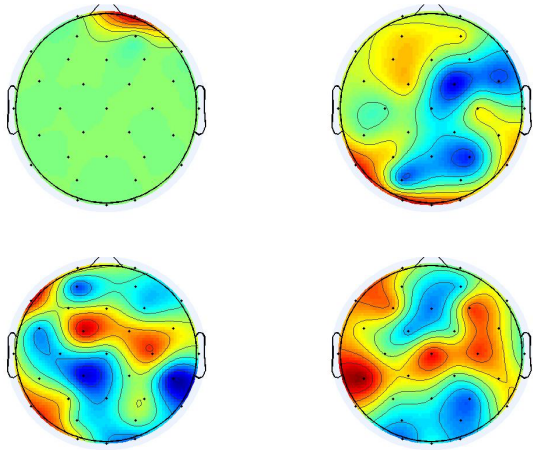

**Fig. 14**. Four components showing the component features

**Multimodal fusion and model optimization for pain classification**

The multimodal fusion system was indicated to be functional (Chang, Bowyer, & Flynn, 2003; Lahat, Adali, & Jutten, 2015; Yang, Lin, & Bhattacharya, 2008). With numerous signals to analyze pain level, a multimodal fusion classification architecture scheme was designed, as shown in **Fig. 15.**

In this experimental setting, we utilized known physiological patterns pertaining to pain perception and train algorithms iteratively for data from multi-modal sources. With learning, feature extraction was applied to physiological modalities to generate pain classifications on a 0-10 scale (0 = No Pain; 10 = Breakthrough Pain). The main goal of the sensor fusion al-

gorithms was to establish a self-improving model for accurate and reliable estimation of pain.

After feature extraction, all features were combined by concatenating individual features to a higher dimensional vector during feature fusion. Then we used the one-versus-the-rest algorithm to perform multi-classification. Each classifier was of two patterns and produces a real-valued confidence score for its decision. All classifiers were trained first. After all the trained classifiers performing classification, the 11 confidence scores were multiplied by 11 weights. The updating process found optimized weight parameters until predicted pain level agrees with true pain level.

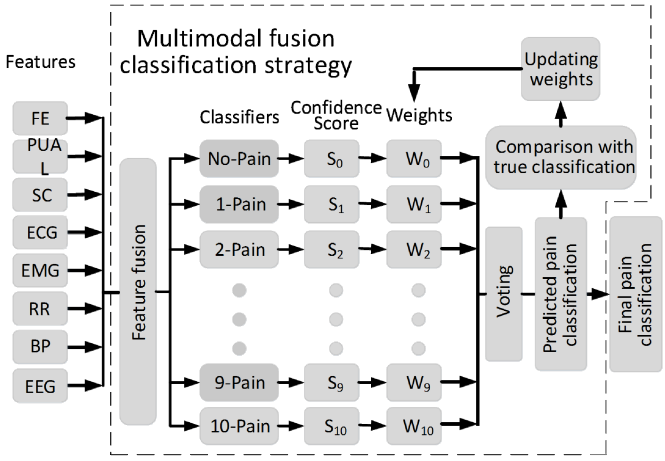


**Fig. 15**. A multimodal fusion classification architecture scheme

The original testing procedure used all physiological sensors. After performing feature selection, it was determined that EMG, respiration rate, skin temperature, and blood pressure did not show a significant impact on the model. Additionally, only two of the nine original EEG channels considered (FP2 and C4) were not shown impactful. For future testing, these sensors and/or features could be used as low priority sensor. The remaining features include skin conductance, heart rate, EEG, facial repression, and PUAL. This reduction would reduce setup time and cost, as well as the invasiveness of the test, and hence improve overall efficiency.

The incremental value of different sensors was suggested to be assessed in objective assessment. For example, under the condition certain signals may be missing or could not be recorded, e.g. eye movement signal, facial expression signal. Another example is that EEG could not be recorded due to certain reasons (discomfort or bandage on the head). In these cases, we assign a confidence score and weight to each sensor to converge outcome in pain assessment

Extreme gradient boosting tree, K-nearest neighbors, Naïve Bayes, neural network, random forest, and support vector machine modeling methods were used. Of all regression models tested, the random forest model and extreme gradient boosting tree were the two bests with regards to error measures. The random forest model was chosen as the final proof-of-concept model over the best-performing classification model. The regression model outputs a specific expected pain value. This pain value will be more practical for doctors to use in a clinical setting, and is less restrictive than the pre-defined pain categories of the classification models. The root mean square error (RMSE) of the random forest model is shown in **Fig. 16.**

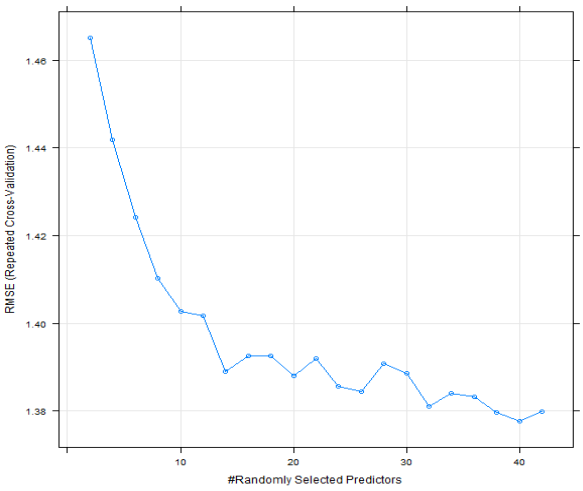


**Fig. 16.** Root Mean Square Error (RMSE) of the random forest model

To optimize the model, it is suggested that the effects of all the above involved sensors would continue to be investigated to study those with possible incremental values.

## RESULTS

Based on this study, it was clear from the topographies that the general trend in initial brain activity was low for the EEG signals. However, brain activity began to gradually increase over the course of the experiment. With regards to the EEG frequency bands, the NIC program was used for signal analysis. It was found that the delta frequency band (0 – 4.0 Hz) exhibited the largest amount of fluctuation and activity across all individuals. Since multiple measures were taken to minimize the influence of noise on the signal, such as eye artifacts, unnecessary motion, and speech, this suggests that the delta frequency band is the ideal frequency range to be used for pain indication.

A one-way analysis of variance was conducted on skin conductance and PUAL. The null hypothesis was tested against $p < 0.05$. The analysis was conducted at a 256Hz sampling rate for all signals. Two male subjects were removed from the analysis due to the limited number of trials (< 2). Skin conductance initially increased in magnitude, then began to decrease over time. Facial expression was shown feasible for pain level assessment. For the Multimodal Sensor modeling, random forest models were the best performing model with an accuracy of 73.67% and extreme gradient boosting tree was close behind with accuracy of 72.98%

## DISCUSSION

The experimental results supported the hypothesis that certain physiological signals are reliable indicators for the presence or absence of pain. Specifically, skin conductance, PUAL, heart rate, facial expression, and EEG were found to

provide meaningful results. Given certain scales and calibration schemes, a pain intensity scale that was based on physiological signals could be developed. EEG data could then be used to support the pain intensity measurement based on the magnitude of brain activity.

It is proposed to use a multi-modal physiological signal method for determining the presence of pain in an individual. First, skin conductance would be used as an initial short term indicator for when a subject experiences pain. The increase in skin conductance in the experiment was likely caused by the initial 'shock' subjects felt when they placed their hand in the ice bucket. Thus, it is suggested that skin conductance should be used for short-term (1-2 min) measurements of pain. EEG should be used for determining pain over a period of time greater than 2 minutes, primarily due to the behavior of the signals where increases in activity are only noticeable after a certain period of time, as shown in **Fig. 13**.

EEG signals can be used more specifically for determining chronic pain, as it is a form of pain that is experienced continuously over an extended period of time. Skin conductance would also play a factor in determining pain intensity in a subject experiencing chronic pain; however, these signals are more suitable in a time-restricted environment. Examples of these environments would be initial triage to a hospital ER or an outpatient clinic.

Baseline measurements as comparison to collected measurements would have to be standardized. Thus, we propose the collection of a large database of human physiological signals that are based on certain age ranges, genders, and ethnic background.

The algorithm for detecting pain should involve the usage of weighting factors assigned to each physiological signal, depending on the environment the subject is being tested in and the duration of the measurement. These weights would influence the final output of the algorithm and output either a 'Pain' or 'No Pain' indicator. Skin conductance results would be given a greater weight on the final outcome of the algorithm in shorter measurements, for example. While the results of EEG would have an increased weight for measurements over 2 minutes. The purpose behind this weighting scheme is to make the algorithm's application robust and applicable to all medical environments, including triage intake, ER, ICU, and outpatient clinics.

Further experimentation is necessary to prove the efficiency of this method; thus, further clinical trials will be conducted within outpatient clinics and hospital settings on both patients experiencing chronic and acute pain. Setting and each type of pain experienced would be tested separately in order to determine proper configurations and the ideal environment for the algorithm. Patient data will be used for the aforementioned algorithm to determine if it is a suitable method for the development of a pain indicator and pain scale.

## CONCLUSION

Based on our current data analysis, EEG, skin conductance, Pupillary Unrest under Ambient Light (PUAL) and facial expression were determined to be good indicators of cold, tonic pain measurement because they exhibited the greatest difference from the baseline measurements. Furthermore, EEG delta band activity increased throughout the course of the experiment. It is predicted that the power of delta bands increases with an increase in pain level. This frequency range should be further investigated under various pain stimuli. It was recommended that these two signals be used to determine prolonged pain experiences such as patients exhibiting pain during ICU or post-operation visits. For short pain experiences or when a quick evaluation of pain intensity is needed, such as during an initial patient assessment, skin conductance are ideal indicators for pain intensity. Due to the small sample size of the population, it is recommended to obtain a larger, homogenous sample in order to minimize outliers and confirm our conclusions. We recommend further study of physiological signals during pressure pain stimulus, as this is also a determinant for short-interval pain.

## ACKNOWLEDGEMENTS

The authors would like to thank all the participants involved in this research study, and the contributions from the Intelligent Human Machine Systems (IHMS) Lab members: Yikang Guo, Mingxin Yu, Kevin Carr, Nicholas DelRe, Keith Fleming, Michael Woulfe, Benjamin Yarsky, and Biren Dalip.

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