Machine Learning Approaches for Pain Detection: Project Proposal

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***Abstract*—We will use physiological signals to detect pain using the BioVid Heat Pain database. The work explores the viability of these signals as a means of detecting pain experiences by patients unable to communicate during therapy.**

***Index Terms*—pain, pain detection, objective measures of pain, machine learning, artificial intelligence, physiological signals**

I. Introduction and Motivation

Patient self-reporting of pain remains the gold standard in patient pain assessment [1], however, when patients are sedated, unresponsive or on a ventilator and unable to effectively communicate, self-reported measures are inadequate to assess and respond to the patient's pain.

The use of physiological signals in the objective assessment of pain has been explored in recent years [1], [2], [3] [4]. Researchers have explored easy-to-obtain signals such as heart rate (HR) and derived heart rate variability (HRV), blood pressure (BP), galvanic skin response (GSR), video imagery of facial expression, and measurement of facial muscle twitch and their correlation with pain experience [1] . Physiological signals from inexpensive photoplethysmography (PPG), electromyography (EMG), and electrocardiogram [1] have been used in measures and algorithms to quantify pain. More recent work have used these signals in machine learning-based classifiers to assess pain [5], [6].

In this study we will predict pain from participant physiological signals including HR and GSR. Using data from the Biovid Heat Pain Database, we will compare various data preprocessing and classifier techniques and assess accuracy of pain detection. We will compare our classifier prediction rates with published studies from Werner et al 2016 [7], Othmen et al 2019 [8], and Lopez-Martinez et al 2017 [9] where facial expression, ECG and EMG signals are included. We will assess whether HR, HRV and GSR provide sufficiently accurate and timely results with classifiers for the target application.

Transient nociceptive pain is short-term pain caused by the stimulation of nociceptors in the skin or tissue. Onset occurs soon after the stimulation is applied [10]. This results in autonomic responses producing changes in HR, HRV, and GSR [2] suggesting these signals can be used to detect pain induced by stimulus during therapy, treatment, or care. For those unable to communicate such as patients living with advanced ALS (amyotrophic lateral sclerosis) and Complete Locked-In Syndrome (CLIS) [11] this could provide a window into their pain experience during care and give clinicians the tools required to personalize care practice. Though autonomic impairment is present in patients with ALS [12] and reduced HRV is associated with mortality as ALS progresses [13], appropriate HRV metrics may exist [14] that can be used to predict acute nociceptive pain. This work will provide insight for selection of physiological signals in pain detection wearable technology for pain monitoring and could provide tools for clinical care.

II. Approach and Methodology

A. Data

In this study we will use the BioVid Heat Pain database is described by Walter et al 2013 [15] and available by request [16]. The data is available for non-commercial research only.

The dataset includes physiological signals (recorded at 512 Hz), video, and 3D camera recordings from 90 research subjects during heat stimulus to elicit pain. Physiological signals such as skin conductance level and electrocardiogram are of most interest in our study as the signal data is most easily and inexpensively collected. Participants were subjected to heat stimulus while the physiological signals and video were recorded. Pain intensity was calibrated on a 5-point scale from the heat stimulus temperature with 32 degrees Celsius set as baseline temperature. The temperature was increased and when the heat stimulus was first experienced as pain it was recorded as Tp. The heat stimulus was increased further and the maximum tolerable temperature was recorded as Tt. The temperature difference between Tp and Tt was further equally divided into three intervals. Each participant was subjected to 20 episodes of stimulation at each pain intensity temperature resulting in 80 recordings with intensity annotations for each participant. For our study we will assume the temperature setting annotation infers pain intensity and attempt to classify the physiological signals based on the pain intensity annotations.

This well-documented dataset has been used in development of various predictive models including Werner et al 2016 [7], Othmen et al 2019 [8], and Lopez-Martinez et al 2017 [9] amongst others.

However, these attempts to assess have focused on facial expressions classification for the purpose of deriving pain annotations. Our study will focus solely on the physiological signals. This maps most closely to our use case, as ALS patients eventually lose control of facial muscles [11] and are unable produce facial expression.

B. Intended Experiments

Gruss 2015 [17] used Support Vector Machines (SVM) using the Biovid data. Our experimentation will replicate the SVM implementation. Furthermore, we will explore deep learning training. By experimenting with different LSTM and CNN layers, we aim to optimize classification accuracy for a minimum training time.

Experiments will include:

- use of MATLAB Classification Learner application to train SVM
- use of MATLAB Deep Network designer to perform deep learning

A deep learning classification approach will be used, as indicated in the literature for time series classification applications [18].A non-linear classifier provides generally better performance with continuous and multi-dimensional features. MATLAB's Deep Learning Toolbox provides a framework for designing and implementing deep neural networks with algorithms, pretrained models, and apps [19]. In our study, we will calculate and compare classification rate (accuracy) sensitivity and specificity and compare them to metrics achieved in Gruss et al 2015 [17].

III. Planning and Milestones

The project team consists of two graduate students. Ms. Sharma (1st year MSc) has past experience developing ML models and pipelines in Matlab. Ms. Ieraci (1st year PhD) has no recent experience in either. Work on the project will be shared equally. The students have collaborated for many years now and meet weekly to discuss approach and assign work, and will use collaboration tools such as Github and Overleaf for code management and documentation.

A. Data Preparation and Pre-Processing, 2 weeks, Oct 4 - Oct 18

- File preparation and visualization
- Signal preprocessing
- Feature extraction

B. Training and Experimentation, 4 weeks, Oct 19 - Nov 15

- SVM model training
- Deep learning model training
- Experimentation to improve accuracy

C. Evaluation, 2 weeks, Nov 16 - Nov 30

- Analysis of classification accuracy based on pain intensity
- Compute receiver operator characteristic curves and confusion matrix
- Classification rate (accuracy) sensitivity and specificity in Gruss et al 2015 [17].
- Evaluation using mean absolute error and root mean square error [6]

D. Wrap-Up and Final Report, 1 week, Dec 1 - Dec 8

- Final report
- Demonstration Video
- Final Submission December 10

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