AUT Jouranl of Modeling and Simulation

AUT J. Model. Simul., 52(2) (2020) 1-10
DOI: 10.22060/miscj.2020.18449.5213

A Physiological-Inspired Classification Strategy to Classify Five Levels of Pain

Somayeh Afrasiabi*, Reza Boostani, Mohammad-Ali Masnadi-Shirazi

School of Electrical & Computer Engineering, Shiraz University, Shiraz, Iran

ABSTRACT: Current research on quantitative pain measurement using the electroencephalogram (EEG) signals showed a promising result just on classifying pain from no-pain states. In this paper, we go one step further introducing pain-level dependent EEG features as well as proposing a physiologically-inspired hierarchical classifier to provide promising results for differentiating five classes of pain. In this research, forty four subjects were voluntarily enrolled, each of whom executed the Cold-Pressor Test (CPT), while their EEGs were simultaneously recorded. We filtered the EEGs through the alpha band and elicited meaningful features to reveal the behavior of signals in terms of distribution, spectrum and complexity at each pain state. To assess the susceptibility of the features in classifying one/group of classes against others, Kruscall-Walis test was applied to give a clue in order to construct the structure of our decision tree, where a Bayesian Optimized support vector machine (BSVM) was trained at each node. After arranging the tree, sequential forward selection (SFS) was applied to select a customized subset of features for each node. Our results provide 93.33% accuracy for the five classes and also generate 99.8% for pain and non-pain classes, which is statistically superior (P<0.05) to state-of-the-art methods over the same dataset.

Review History:

Received: 2020-05-17
Revised: 2020-07-22
Accepted: 2020-09-24
Available Online 2020-12-01:

Keywords:

Pain measurement
Physiological based classifier
EEG signal processing
distribution of alpha band

1.INTRODUCTION

Nowadays, pain is considered as the fifth vital sign, after body temperature, heart rate, respiratory rate and blood pressure [2].Precise and continuous measuring of pain is critical, especially in patients who are intubated, patients under painful surgical operation, patients admitted in the intensive care unit (ICU) and totally for those who cannot announce their pain. Consequently, the need for developing a reliable, accurate and automatic pain measuring system is serious in order to prevent inadequate or suboptimal treatment of pain in these subjects.

The most common pain measuring tools are visual analog scales (VAS), numerical rating scales (NRS) and verbal rating scales (VRS) [3]. Nonetheless, these subjective measures do not use any physiological based data and therefore, it may impose a degree of uncertainty in terms of their dependency to the subjects. Despite many studies that have been done in this field, precise and automatic quantifying the amount of feelings and perceptions of each individual from pain is still an unsolved issue.

Since the field of automatic pain measuring is an interdisciplinary study that involves the selection and examination of several parameters, previous studies are being reviewed in three different areas including:

A. BRAIN VISUALIZATION TECHNIQUES:

By observing the functional brain images, it is evident that the pain is felt in the brain [4]. Therefore most studies in this field benefit from one or more brain mapping techniques. Among these techniques, Functional Magnetic Resonance Imaging (fMRI) is mainly used for the purpose of localization of pain related sources [5, 6]. MR Spectroscopy and Near Infrared Spectroscopy (NIRS) are recently used for pain detection by tracking the long term changes in brain chemistry or cerebral hemodynamic activity [7]. Although some attempts have been made to functionally analyze the brain changes through the pain by nuclear scanning techniques [4], they neither present the pain related temporal information nor give a specified location of pain sources in the brain.

Using Electroencephalogram (EEG) signal in pain study field is recently increased [4, 8-11]. Taking into account the high temporal resolution of electroencephalogram (EEG) signals, analysis of EEG seems to provide online physiological-based data to quantitatively track the dynamic changes in pain sensation.

B. PAINFUL STIMULUS:

In the past two decades, in order to study pain, the brain's response to the painful stimulus has been extensively investigated. Several stimuli have also been used as painful stimuli, such as electrical [7], mechanical [12] and thermal (both in the form of cold [8, 13] and heat [14, 15]) stimulus. The main purpose of painful stimulation is to stimulate

*Corresponding author's email: * afrasiabi@cse.shirazu.ac.ir

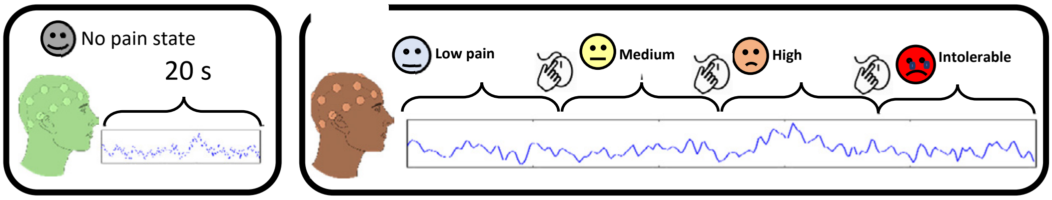

Fig. 1. The diagram of the pain EEG recording Experiment.

the experience of real and clinical pain. Consequently, an overdrive or a brief stimuli is not enough for this purpose, even for studying acute pain [8]. Meanwhile, tonic pain models have been shown to stimulate clinical pains better than phasic pain models [10]. The most popular tonic pain stimulator in recent studies is thermal stimulator due to its lowest side effects. Cold Pressor Test (CPT) (which is the most popular thermal stimulator) is performed by immersing the hand into an ice water container in order to measure the pain threshold and pain tolerance [4, 8, 10, 13].

C. EEG ANALYSIS:

So far, in order to recognize the pain feeling from EEG signal, several complex temporal-spectral-spatial patterns of it has been suggested and investigated. Pain-related evoked potentials (Eps) are well-known modality in pain detection [16]. The reason is that the pain stimuli evoke, increases neural activity between 150 to 400 milliseconds after stimulus [17]. High overlap between many components of the Eps and the alpha band of EEG (8-12 Hz) is the most challenging problem in this area. Eps are very informative features although they are not characterized in order to extract all pain related information as they deserve [13].

Since during pain feeling, the neurons are activated more asynchronously, the integration of their activities will result in more rough oscillations. This fact is the base for studies who use complexity measures such as fractal dimension (e.g., Katz, higuchi), Shannon entropy and approximate entropy (ApEn) to provide their pain related feature vector [13, 18]. Although the mentioned features are proper descriptors of rough signals, they need a long time interval of data to be calculated accurately (which is not available especially for low pain tolerant subjects).

Wavelet transform is also used in order to extract time-frequency representation of EEG in painful conditions [8, 19]. The concept of wavelet higher-order spectral (WHOS) features, is also shown as a potential field to reflect the nonlinear behavior of EEG signal and its changes in pain and no-pain states [8].

In different studies, pain related changes in the features extracted from all different frequency bands of EEG, have been observed via band power feature [9-11, 13-15]. However the significance of each band for pain is still unknown.

In most of these studies alpha band is proposed as the most informative band for measuring inter subject pain susceptibility and intra subject objective pain amount along with one or two of other EEG bands like delta and beta or gamma. This is reasonable because alpha brain waves are generally associated with relaxation and contemplation which significantly undergo changes during painful stimulation [10].

Studies performed so far have tried to find a statistical correlation among the extracted features and the change in the state of pain. Some of them present their results in terms of a two class (pain vs no-pain) classification accuracy [5, 8, 9, 16]. There are only a few papers which also distinguish between different amounts of pain [6, 13, 20].

In this paper, we tried to more deeply investigate the alpha band and its role in determining the amount of pain. The research resulted in providing a robust and generalized index for distinguishing five levels of pain. Due to the obtained promising results, our hypothesis that the tonic cold pain induces change to the amount of Gaussianity of PDF of alpha band of the subjects EEG signal, has been proved. Also it has been shown that the amount of deviation from Gaussianity is correlated with the amount of pain sensation. In this regard, a hierarchical classifier was designed using the physiological information changes over the time. The parameters of the SVM based classifier optimized using Bayesian Optimization method. The results of our method is statistically superior to former state of the art pain classification results in all different scenarios such as pain VS no-pain (two class scenario), three class, four class and five class (no-pain, low, medium, high and intolerable pain) .

2.MATERIALS AND METHODS

2-1- Subjects and EEG Recording

44 healthy right-handed volunteers with a mean age of 25 year's old including 24 males and 20 females participated in this study. Their EEG signal were collected during CPT. Scalp EEG signals were recorded at 250 Hz using 34 silver electrodes via a Scan-LT EEG recording apparatus.

Pain condition imposed using bucket of ice water (1.7±0.2 centigrade). Prior to recording, the considered five levels of pain, were described to the subjects using Wong-Baker Faces Pain Rating Scale [21], in order to help them to determine how to rate their pain.

The baseline EEG, where no stimulation and no pain was applied, was recorded at the no-pain phase for 30 seconds. The pain process started as the subject submerged his/her hand into the water which result in a moderate uncomfortable feeling (labeled as low pain). As the unpleasant sensation of pain gradually increased over time, the participants rated their pain at four different levels (low, medium, high and intolerable) according to their practice in the training phase. The subjects marked the levels by clicking a mouse button connected to the recording computer using their left hand. Each mouse click indicated the end of a level and beginning of the next state, except for the intolerable state which its end was shown by the withdrawal of the subject's hand from the water. The timing diagram of the pain EEG recording experiment is shown in Fig. 1.

As the result, recorded signals were labeled based on five classes of pain (rest state and low, medium, high and intolerable pain states), and provided for full review.

To avoid the bias of the results in favor of the class with longer interval of time, the length of "no pain" state was set to average length of the recording EEG in other pain states. The average length of date recorded in each pain state was about 20 seconds.

2-2- EEG Preprocessing

The recorded data passed through a band pass filter (5th order Butterworth), with cut-off frequencies of 0.5 and 70 Hz to remove the baseline drift, linear trend and high frequency noises such as muscle contraction artifact. Line noise at 50 Hz was filtered out using a sharp notch filter.

In order to clean the blink effect, eye movement, neck and scalp muscle movement and sensor movement artifacts and any other non-brain signal from EEG, Artifact Subspace Reconstruction (ASR) [22] was used. The analysis was performed using MATLAB native toolboxes and EEGLAB [23].

2-3-Feature Extraction

According to several studies, amplitude densities of human alpha rhythm in rest and normal states, closely approximate a Gaussian distribution. On the other hand, considerable deviation from Gaussianity in PDF of alpha band of EEG signals through performing a mental task or using certain types of medications has been reported [24].

In this paper, we show that painful stimulation can also have the same result. Also, changes in the amount of Gaussianity in human alpha rhythm concomitant with increase in pain amount using the following features have been investigated and used in order to classify five different pain levels:

1) First to Fourth Order Momentums: Mean (μ), variance $\left(\sigma^2\right)$, skewness and Kurtosis are recognized as the first to the fourth order momentums of x, though skewness and kurtosis are the normalized version of the third and fourth momentums, described as follows:

$$skew(x) = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^3}{\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2}\right)^3} \tag{1}$$

$$kurto(x) = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^4}{\left(\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2\right)^2} \tag{2}$$

The skewness for a normal distribution is zero, and to some extent, any symmetric data should have a skewness near zero. Negative and positive values for the skewness indicate data that are skewed to the left or right side, respectively [25].

2) Range: In statistics and mathematics, the range is the difference between the maximum and the minimum values of a dataset and serves as one of two important features of a data set (including the center and the spread of the data).

Given the statistics:

$$y_1 = \min_j x_j \tag{3}$$

$$y_n = \max_j x_j \tag{4}$$

(among j data samples), the formula for range is:

$$R = y_n - y_1 \tag{5}$$

which provides us with a better understanding of how variate the samples of a dataset [26].

3) Quantile: The quantiles are values which divide a distribution into a certain proportion of observations. Also a Q-Q plot, is a probability plot for comparing two probability distribution by plotting their quantiles against each other. If both distributions behave similar, the points in the Q-Q plot will approximately lie on the line $y = x$.

4) Negentropy: The entropy H of a random vector y with density $P_x(\eta)$ is defined as:

$$H(X) = -\int p_x(\eta)\log p_x(\eta)\,d\eta \tag{6}$$

A fundamental result of information theory is that a Gaussian variable has the largest entropy among all random variables with equal variance. In other words, the Gaussian distribution is the most random (the least structured of all distributions); therefore, entropy index can be used as a measure of Non-Gaussianity.

Normalized version for differential entropy is called negentropy, which is always a nonnegative value, and is zero just for a Gaussian variable. Negentropy is defined as:

Table 1. Features Extracted from Alpha Rhythms of EEG

No.	Feature set	No.	Feature set
1	Mean (MN)	7	Median (.5 Quantile)(MD)
2	Trimmed Mean (TM)	8	Skewness (SK)
3	StandardDeviation (SD)	9	Kurtosis (KU)
4	Trimmed SD (TSD)	10	α band power (BP)
5	Variance (VC)	11	Area under curve (AU)
6	Negentropy (NT)	12	Range (RA)

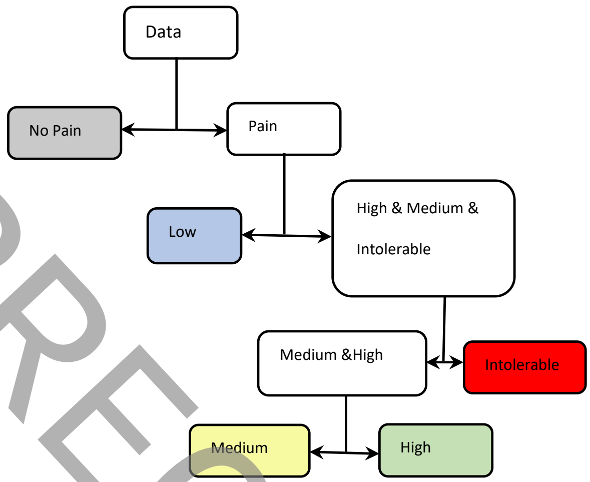

Fig. 2. Structure of proposed hierarchical BSVM classifier

$$J(X) = H(X_{gauss}) - H(X) \quad (7)$$

where X_{gauss} is a Gaussian random vector with the same correlation and covariance matrix as X. Negentropy is also invariant for invertible linear transformations [27].

5) Trimmed mean (TM) and Standard Deviation (TSD): TM and TSD are similar to a mean and SD, but with trimmed (truncated) outliers.

The trimmed version of this statistics, can often be a better fit for datasets with extremely skewed distributions. On the other hand we kept both arithmetic and trimmed estimators to examine the effect of eliminating the outliers on the classification ability of the features.

In this paper, 5% trimmed Mean and SD is obtained by discarding five percent highest and lowest observation in each epoch as follows:

$$TM = \frac{\sum x_i}{n} = \frac{sum\ of\ the\ trimmed\ set}{total\ numbers\ in\ trimmed\ set} \quad (8)$$

$$TSD = \sqrt{\frac{\sum (x_i - TM)^2}{n-1}} \quad (9)$$

The list of all features are presented in Table 1.

2-4- Feature Selection

Our approach in this study is based on the assumption that the distribution of the data varies at different levels of pain. Since the goal of this study is to differentiate five levels of pain states, ANOVA, which is a statistical technique for comparing more than two populations, seems to be more suitable.

The statistical significance of the extracted features is examined using the Kruskal-Wallis test [28], which is a method for one-way ANOVA. The features with $p < 0.01$ are selected as the most significant features, since they reject the null hypothesis of coming from the same distribution.

The sequential forward selection (SFS) search strategy [13] was then used to select a proper subset of features that finely predict the pain levels.

Table 2. Five Best Channels with Best Classification Accuracy

Group of classes	Channels
Pain vs. No-Pain	Fz, P4, Pz, O2 & F4
Low vs. Medium, High & Intolerable	P4, Fz, O2,O1 & P8
Intolerable vs. Medium & High	P4, Fz, FP1, O1 & O2
High vs. Medium	P4, Fz, Fp1,O1 & O2

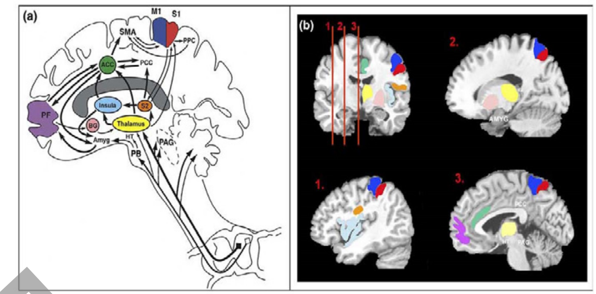

Fig. 3. Cortical and sub-cortical pain perception sources. (a) The pain perception regions and their interconnectivity. (b) The areas shown in an anatomical MRI. (The schematic is modified from[1])

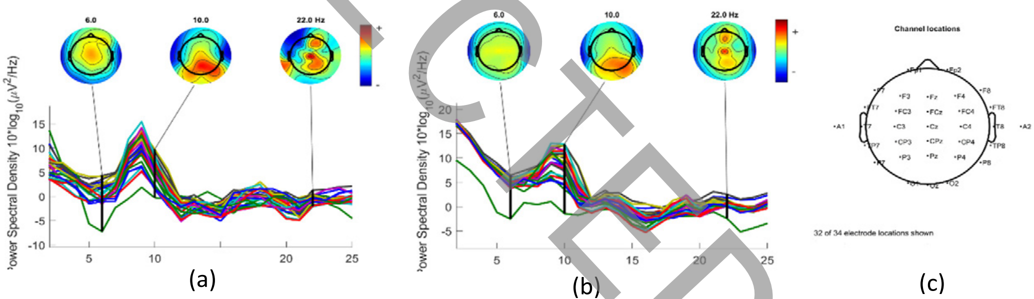

Fig. 4. All 34 channels Power Spectral Density (PSD) and the related brain map in Theta (è) (centered at 6 Hz), Alpha (á) (centered at 10 Hz) and Beta (â) (Centered at 22 Hz) frequency bands, (a) In no-pain state, (b) average of all different levels of pain. (c)Electrode placement locations on scalp.

2-5- Classification Using Bayes Optimized SVM

Support Vector Machines (SVMs), one of the most commonly used classifiers in this field, was employed in the current study. In order to properly choose the kernel function parameters$(\boldsymbol{x})$, such as the regularization strength C or the width of the RBF kernel γ (commonly known as SVM hyper-parameters), the Bayesian optimization is deployed.

This optimization problem can be considered as the process of finding the maximum of $f(x)$, defined as:

$$\boldsymbol{F}(\boldsymbol{x}) = \max_{w} \mathcal{S}\left(w \middle| \{(e_i.y_i)\}_{i=1}^{N}.\boldsymbol{x}\right) \tag{10}$$

where $\{(e_i.y_i)\}_{i=1}^{N}$ (with e_i representing EEG samples features and y_i being the pain level assignment) is the training set, and the goal is to build a predictive model (w) based on these data and hyper-parameters that maximizes the performance score ($\mathcal{S}$). Since $\boldsymbol{F}$ is an unknown function, its gradient, Hessian or any other derivations that could guide the optimization process, cannot be computed. The only action that can be done is to obtain some values for $\boldsymbol{F}$ ($f(x_i)$) at some arbitrary given points x_i ($x_1 : x_t$). Using Bayesian optimization, a global statistical model of this unknown objective function will be developed iteratively.

The best hyper-parameters that separate the two pain

Table 3. The Best Features in a Descending Order for each Node of the Hierarchical Classifier

Classified groups	The best features in terms of accuracy, respectively
No-pain VS. Pain	TSD, SD, RA,MD, KU, BP, VC, TM, SK, MN, NT, AU
Low vs. medium, high & intolerable pain	VC, RA, MN,TM, AU, NT, MD, BP, TSD, SK, SD, KU
Intolerable vs. high & medium	AU, NT, VC, MD, KU, SK, TSD, TM, SD, RA, MN, BP
High vs. medium	SD, RA, TSD, SK, TM, KU, MN, VC,MD, BP, AU, NT

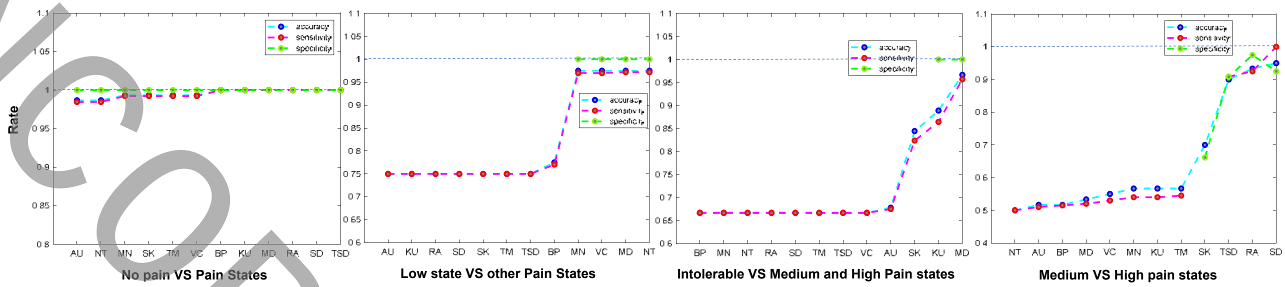

Fig5. The impact level of each feature is shown, using terms: accuracy, sensitivity and specificity. The plots are sorted according to accuracy results and the results for each feature are calculated individually.

Table 4. Different N-Class Classification Problems Considered in This Paper

Classification	Pain & No-Pain states
5-class problem	no-pain, low, medium, high & intolerable
4-class problem	no-pain, low, high & intolerable
3-class problem	No-pain, low & high
2-class problem	No-pain &pain

and non-pain states, are not necessarily the best parameters to separate intolerable pain from low pain state (or other states).therefore, four different Bays Optimized SVM (BSVM) models with different hyper parameters were created during the training phase. Then the hierarchical data-driven classification strategy (shown in Fig. 2) is used as a flexible decision tree in order to classify the EEG features into five different classes. As it can be seen, a group of classes are classified from another group in each node of the tree (Fig. 2).

3- RESULTS

As discussed in part 3, the EEG data in this study is a 34-channel dataset, and also according to Table 2, twelve different features were extracted from the whole signal in five different states.

Using all channels and features in classification did not result in significant improvement in classification accuracy, while it increased the complexity of the problem unreasonably. Therefore, first we tried to sort the most statistically significant channels and features. Our findings imply that the most participated brain regions involved in different pain levels are located below the channels reported in Table 2. As we see, there are three channels (Fz, P4 and O2), which their elicited features are among the highest differentiative features in all pain classes. In addition, these EEG channels are either located above the pain perception sources (Fig. 3) or placed over the highlighted alpha band activation regions, shown in Fig. 4.

Kruskal-Wallis statistical test was then used to discard the non-significant features, which result in $P > 0.01$ (for two by two classes). Table 3. Shows the best features in each node of the classifier in a descending order. The different order of features in different nodes, again confirms the need for a hierarchical classifier. The classification results obtained using each feature individually is shown in Fig. 5.

Finally after sorting the features according to Table 3 in each node of the BSVM classifier, sequential forward selection was applied to select the most descriptive subset of features.

Four different scenarios are designed for practical situations, in which a specialist needs to know his patient suffers from the pain or not and into some extent requires more detailed information about the intensity of pain. As an example, more detailed information about the pain intensity specifically is needed in studies about cognitive appraisal of pain. The decision nodes of the proposed classifier (as shown in fig 2) provide general to specific quantitative diagnosis information in a hierarchical manner to address different requirements.

Table 5. Comparison of Existing State of the Art Pain State Classification Problems.

Source	Modality	$\overline{AC}$	
		Intra-subject	Inter-subject
Huang et al., 2013 [29] [2-class]	EEG	80.3	86.3
Hadjileontiadis et al., 2015 [8] [2-class]	EEG	-	90.25
Broderson et al. 2012 [5] [2-class]	FMRI	66.5	-
Misra et al. 2017 [30] [2-class]	EEG	90	
Current Method [2-class]	EEG	99.82	99.9
Marquand et al. 2010 [31] [3-class]	FMRI	72.67	-
Nezam et al. , 2018 [13][3-class]	EEG	83	-
Current method [3-class](no-pain, low & high pain)	EEG	98.6	98
Current method [4-class](no-pain, low, medium & high pain)	EEG	96	95.7
Nezam et al., 2018 [13] [5-class]	EEG	62	-
Current method [5-class]	EEG	93.33	92.4

Table 6: Classification performance for different sub-problems & the features used in each case.

Classified states	$\overline{AC} \pm std(\%)$	Selected features
No-pain VS. Pain	99.82±0.1	TSD, SD, IRA, MD, KU, BP
Low VS. medium, high &intolerable	97.5 ±2.1	All features except AU
Intolerable VS. medium & high	96.66±3.1	All features except BP
Medium VS. high	93.33±6.4	All features Except NT

The multiclass classification problems considered here are given in Table 4. Additionally we tried to classify pain states in both inter- subject and intra-subject levels. To optimize the parameters of BSVM models for intra-subject classification, the feature vectors of 10 subjects out of 44 were randomly selected as the test data. The BSVMs were trained via 10-times 10-fold cross validation method, over the train set. Afterward the trained BSVMs were used to classify the pain levels of the test subjects.

The final classification result of the proposed method along with the other state of the art studies is presented in Table 5. Which shows the superiority of our results compared with others.

4- DISCUSSION

4-1- Comparative Study

In the current study, we collected EEG data during an experimental paradigm in which subjects experienced and reported five different levels of pain. We implemented a novel field for the formation of quantitative features that could characterize tonic cold pain objectively. In this approach, twelve different features were used to determine whether the deviation of PDF of alpha band from Gaussianity contributes to quantify pain perception. By using this method, remarkable results were achieved and we report 3 novel findings. First a new hierarchical SVM based classifier is designed whose parameters are optimized using Bayesian optimization.

Table 7. Comparison of different classifiers with the proposed hierarchical Bayes-optimized SVM classifier.

Classifier / Resolution	multi-class SVM	Bagging	KNN	Proposed Classifier
Two-class	89.3	86.67	80.1	99.82
Three-class	69.7	64.44	61.2	98.6
Four-class	46.5	51	47.67	96
Five-class	36.3	43.2	28.9	93.33

Second, this hypothesis has been confirmed that tonic cold pain induced widespread changes to the PDF of alpha band of EEG signal and the deviation from Gaussianity increases with the amount of pain sensation. Third, we outperformed previous classification results in all scenarios (two class, three class, four class and five class) in both inter-subject and intra-subject states.Table 5, compares the obtained results of current study to some of existing state of the art methods which report the accuracy of their methods numerically and quantitatively.

While such studies have had a fair amount of success, most of them examined the efficacy of a two-class version of this problem. Along with increasing the number of classified levels of pain, our method outperformed formers in all two, three, four and five class scenarios. This achievement is the result of the choosing suitable features along with appropriate classifier design.

4-2- Effective and non-Complex Features

In contrast to the previous attempts that applied a transform on the EEG signals and feed the coefficients of that transform to a classifier, here we characterized a narrow band of EEGs by 12 informative features. In other words, if we extracted these features from the raw EEGs, these significant results could not be achieved. It means that the other bands of EEGs (except the alpha band) generate redundant features that mislead the pain level classification problem. Among the extracted features, measuring the distribution deviation response to different levels of pain has the most important role. This is therefore pain related evoke potential patterns are appeared in the EEGs in response to the external pain and the band width of these patterns is common with the alpha band. Therefore, adding these patterns to the background EEG deteriorate the distribution of the EEGs, specifically in the alpha band. The results show that the deterioration of this distribution varies from one level of pain to another one.

As an example, for classifying the high pain state against the medium, SD, RA and TSD present relevant information rather than BP, AU and NT. Thus, jumps between the successive samples can be better explained via standard deviation, range and TSD while a signal with uniform amplitude can have a high band power (BP) and area under curve (AU). In addition, NT value is mostly dependent on the distribution of amplitudes and is not influenced by local fast alternations in the signal. Although in the no-pain state, the alpha band distribution is Gaussian-like, by increasing the amount of pain feeling, the distribution is deformed and therefore, the skewness and Kurtosis of the signals can represent the amount of this variation. The classification results of the scenarios explained in Table 4, are illustrated in Table 6. Although for low pain tolerant subjects the transition between the pain states is rapidly occurred and we encounter with small sample size problem, the proposed scheme by the help of BSVM overcome this shortcoming and provide promising results.

As an example, for classifying the high pain state against the medium, SD, RA and TSD present relevant information rather than BP, AU and NT. Thus, jumps between the successive samples can be better explained via standard deviation, range and TSD while a signal with uniform amplitude can have a high band power (BP) and area under curve (AU). In addition, NT value is mostly dependent on the distribution of amplitudes and is not influenced by local fast alternations in the signal. Although in the no-pain state, the alpha band distribution is Gaussian-like, by increasing the amount of pain feeling, the distribution is deformed and therefore, the skewness and Kurtosis of the signals can represent the amount of this variation. The classification results of the scenarios explained in Table 4, are illustrated in Table 6. Although for low pain tolerant subjects the transition between the pain states is rapidly occurred and we encounter with small sample size problem, the proposed scheme by the help of BSVM overcome this shortcoming and provide promising results.

4-3- Classification Procedure

To distinguish the pain classes, several classifiers have been adopted, among which bagging [16], k-Nearest Neighbors [8, 13], Discriminant Analysis and SVM [5, 8, 13] have provided convincing results for two class problems. According to table 7 although these methods have some success in two class or even three class problem, their results decline rapidly as the number of classes increase to five. The better performance of proposed hierarchical BSVM classifier over previous methods is due to the following reasons:

1. The effectiveness of a classifier derived from SVMs is highly dependent on a proper selection of its kernel function and parameters [32]. The parameters of the kernel SVM include the regularization parameter (C: is the upper bound of the Lagrange coefficients) and the variance (γ) of the RBF kernel that commonly known as SVM hyper-parameters. These hyper-parameters must be estimated from the data in order to maximize the classification performance. Using Bayesian optimization to estimate the hyper-parameters, results in a better performance rather estimating these parameters using heuristic searching methods. By this scheme, the SVMs located in the decision tree nodes are all optimized with regard to the

selected subsets of features for the corresponding node.

2. The second supremacy is due to distributing the whole decision making into some simpler classification tasks with lower number of classes, where each classifier takes a customized subset of features. This is because the classification of all classes with a single classifier is impossible. Since a high overlap naturally exists between the similar classes like (low and moderate), (moderate and high) and (high and intolerable). Some features might be able to differentiate one or two of the three above cases not all of them. Consequently, for differentiating different classes, different subsets of features are needed.

4-4-Study Limitations and Future Work

Pain is a sensation that everyone uniquely experiences and feels it and therefore people might report different pain level in response to a certain value of pain stimuli. Also the endurance of different people to deal with painful stimulation varies significantly. In most cases individuals agree about the existence or absence of pain (two class problem); while when the number of pain levels is increased the disagreement in their pain report is increased due to the natural difference in their pain tolerance. Although some people report the same amount of pain as medium level, some others label it as high level. Lower classification results in these two states, is the result of subjective labeling of their EEG signal. On the other hand, due to lack of a standard dataset in this field, most of the research groups work on the data recorded by themselves. Thus, it is impossible to compare the results of different studies, unless they are all applied to the same dataset.

Based on the above mentioned items, as a future work collecting a multimodal biomedical dataset containing EEG signal and other related physiological data (e.g., heart and breath rate), for assigning accurate label to the intervals of data over a vast group of subjects is deemed necessary.

5- CONCLUSION

In this research, by comprehensive decoding the alpha band content, we remarkably improved the classification accuracy of pain levels by proposing a novel physiological inspired classifier. Regarding the variety of elicited EEG features in the alpha band, consistent features were selected by the SFS method and by investigating the distribution of these features and considering a subset of features for each node, the candidate classes were chosen at the corresponding node. Empirical results imply the reachability of the alpha band in discriminating five levels of pain with a considerable improvement compared to the counterparts. As the future work, we suggest to build a universal decision tree for a considerable number of subjects which can be adapted and customized for each new participants. In addition, incorporating the features of electrocardiography can enhance the differentiating rate among the classes.

6- REFERENCES

[1] A. Apkarian, M.C. Bushnell, R. Treede, J. Zubieta, Human Brain Mechanisms of Pain Perception and Regulation in Health and Disease, Eur J Pain, 9(4) (2005) 463-484.
[2] M. McCaffery, C.L. Pasero, Pain ratings: the fifth vital sign, Am J Nurs, 97(2) (1997) 15-16.
[3] J. Shieh, C. Dai, Y. Wen, W. Sun, A Novel Fuzzy Pain Demand Index Derived From Patient-Controlled Analgesia for Postoperative Pain, IEEE Transactions on Biomedical Engineering, 54(12) (2007) 2123-2132.
[4] A.V. Apkarian, M.C. Bushnell, R.-D. Treede, J.-K. Zubieta, Human brain mechanisms of pain perception and regulation in health and disease, European Journal of Pain 9(2005) 463-484.
[5] K. Broderson, K. Wiech, E. Lomakina, C. Lin, J. Buhman, U. Bingel, M. Ploner, K. Stephan, I. Tracey, Decoding the Perception of Pain from FMRI Using Multivariate Pattern Analysis, Neuroimage, 63(3) (2012) 1162-1170.
[6] A. Marquand, M. Howard, M. Brammer, C. Chu, S. Coen, J. Mourao-Miranda, Quantitative prediction of subjective pain intensity from whole-brain fMRI data using Gaussian processes, Neuroimage, 49(3) (2010) 2178-2189.
[7] M.A. Yukel, C.A. Aasted, M.P. Petcov, D. Borsook, D.A. Boas, Specificity of hemodynamic brain responce to painful stimuli: a functional near infrared spectroscopy study, Nature, Scientific Reports, 5(9469) (2015) 1-9.
[8] L.J. Hadjileontiadis, EEG Based Tonic Cold Pain Characterization Using Wavelet Higher order Spectral Features, IEEE Transactions on Biomedical Engineering, 62(8) (2015) 1981-1991.
[9] G. Misra, W.E. Wang, D.B. Archer, A. Roy, S.A. Coombes, Automated classification of pain perception using high-density electroencephalography data, J Neurophysiol, 117(2) (2017) 786-795.
[10] R.R. Nir, R. Lev, R. Moont, Y. Granovsky, E. Sprecher, Neurophysiology of the Cortical Pain Network: Revisiting the Role of S1 in Subjective Pain Perception Via Standardized Low-Resolution Brain Electromagnetic Tomography (sLORETA), The Journal of Pain, 9(11) (2008) 1058-1069.
[11] F. Razavipour, R. Boostani, S. Kouchaki, S. Afrasiabi, Comparative Application of Non-negative Decomposition Methods in Classifying Fatigue and Non-fatigue States, Arabian Journal for Science and Engineering, 39(10) (2014) 7049-7058.
[12] M. Fabri, G. Polonara, A. Quattrini, U. Salvolini, Mechanical Noxious Stimuli Cause Bilateral Activation of Parietal Operculum in Callosotomized Subjects, Cereb. Cortex, 12(4) (2002) 446-451.
[13] T. Nezam, R. Boostani, V. Abootalebi, K. Rastegar, A Novel Classification Strategy to Distinguish Five Levels of Pain Using the EEG Signal Features, IEEE Transactions on Affective Computing, (2018) 1-9.
[14] M. Huber, J. Bartling, D. Pachur, S. Woikowski, S. Lautenbacher, EEG Responce to Tonic Heat Pain, Exp. Brain Res. , 173(1) (2006) 14-24.
[15] C. Huishi Zhang, A. Sohrabpour, Y. Lu, B. He, Spectral and spatial changes of brain rhythmic activity in response to the sustained thermal pain stimulation, Human brain mapping, 37(8) (2016) 2976-2991.
[16] G. Huang, P. Xiao, Y. Huang, G. Iannetti, Z. Zhang, L. Hu, A Novel Approach to Predict Subjective Pain Perception from Single-trial Laser-evoked Potentials, Neuroimage, 1(81) (2013) 283-293.
[17] S. Afrasiabi, R. Boostani, S. Koochaki, F. Zand, Presenting an effective EEG-based index to monitor the depth of anesthesia, in: The 16th CSI International Symposium on Artificial Intelligence and Signal Processing (AISP 2012), 2012, pp. 557-562.
[18] M. Vatankhah, V. Asadpour, R. Fazelrezai, Perceptual Pain Classification Using ANFIS Adapted RBF Kernel Support Vector Machine for Terapeutic Usage, Applied Soft Computing, 13(1) (2013) 2537-2546.
[19] M. Vatankhah, A. Toliyat, Pain Level Measurment Using Descrete Wavelet Transform, IJET, 8(5) (2016) 380-385.
[20] E. Schulz, E.S. May, M. Postorino, L. Tiemann, M.M. Nickel, V. Witkovsky, P. Schmidt, J. Gross, M. Ploner, Prefrontal Gamma Oscillations Encode Tonic Pain in Humans, Cereb Cortex, 25(11) (2015) 4407-4414.
[21] G. Garra, A.J. Singer, A. Domingo, H.C. Thode, Jr., The Wong-Baker pain FACES scale measures pain, not fear, Pediatr Emerg Care, 29(1) (2013) 17-20.
[22] F. AliMardani, R. Boostani, B. Blankertz, Presenting a Spatial-Geometric EEG Feature to Classify BMD and Schizophrenic Patients, 2016, 5(2) (2016) 7.
[23] A. Delorme, S. Makeig, EEGLAB: an open source toolbox for analysis of

single-trial EEG dynamics including independent component analysis, J Neurosci Methods, 134(1) (2004) 9-21.
[24] R. Elul, Gaussian behavior of the electroencephalogram: changes during performance of mental task, Science, 164(3877) (1969) 328-331.
[25] S. Afrasiabi, R. Boostani, F. Zand, F. Razavipour, INTRODUCING A NOVEL INDEX FOR MEASURING DEPTH OF ANESTHESIA BASED ON VISUAL EVOKED POTENTIAL (VEP) FEATURES, Iranian Journal of Science and Technology Transactions of Electrical Engineering, 36(2) (2012) 131-146.
[26] H.O. Hartley, H.A. David, Universal Bounds for Mean Range and Extreme Observation, The annals of Mathematical Statistics, 25(1) (1954) 85-99.
[27] A.D. Nazhvani, R. Boostani, S. Afrasiabi, K. Sadatnezhad, Classification of ADHD and BMD patients using visual evoked potential, Clinical Neurology and Neurosurgery, 115(11) (2013) 2329-2335.
[28] S. Afrasiabi, R. Boostani, M.-A. Masnadi-Shirazi, A Physiological-Inspired Classification Strategy to Classify Five Levels of Pain in: ICBME2019, Tehran, 2019.
[29] G. Huang, P. Xiao, Y. Hung, G. Iannetti, Z. Zhang, L. Hu, A Novel Approach to Predict Subjective Pain Perception from Single-Trial Laser-evoked Pottential, Neuroimage, 1(81) (2013) 283-293.
[30] G. Misra, W. Wang, D. Archer, A. Roy, S. Coombes, Automated Classification of Pain Perception using High density Electroencephalography Data, Neurophysiology, 117 (2017) 786-795.
[31] A. Marquand, M. Hovard, M. Brammer, C. Chu, S. Coen, J. Mourao-Miranda, Quantitative Prediction of Subjective Pain Intensity from whole brain FMRI Data Using Gaussian Processes, Neuroimage, 49(3) (2010) 2178-2189.
[32] J. Bergstra, Y. Bengio, Random Search for Hyper-parameter Optimization, J. Mach. Learn. Res., 13(1) (2012) 281-305.

HOW TO CITE THIS ARTICLE

S. Afrasiabi, R. Boostani, M.Masnadi-Shirazi, A Physiological-Inspired Classification Strategy to Classify Five Levels of Pain, AUT J. Model. Simul., 52(2) (2020) 1-10.

DOI: 10.22060/miscj.2020.18449.5213