Finding Patterns in Biological Parameters

Suja Panicker
Assistant Professor, Dept. of Computer Engineering
Maharashtra Institute of Technology, Pune
Pune, India
suja.panicker@mitpune.edu.in

Shruti Bhujange
Dept. of Computer Engineering
Maharashtra Institute of Technology, Pune
Pune, India
shrutibhujange@gmail.com

Shraddha Karne
Dept. of Computer Engineering
Maharashtra Institute of Technology, Pune
Pune, India
shraddhakarne33@gmail.com

Reshma Kadam
Dept. of Computer Engineering
Maharashtra Institute of Technology, Pune
Pune, India
kadam.reshma700@gmail.com

***Abstract*—**Changes or variation occur in physiological parameters of the body when a person is going through a tough time or he is extremely happy. These changes in physiological parameters can be used for detecting emotions. Emotional computing is a field of Human Computer Interaction(HCI) where we detect human emotions. Emotion recognition based on affective physiological changes is a pattern recognition problem, and selecting specific physiological signals is necessary and helpful to recognize the emotions. In this paper, we have discussed various research papers analysing that how emotions are detected from physiological signals using non-invasive methods. Developers use various Data Mining techniques for developing such results. Heart Rate Variability(HRV), Skin Temperature(ST), Blood Volume Pulse(BVP) are the main highlights as these are key parameters in Physiological signals.

Keywords- *Data Mining, Emotion Detection, Physiological signals.*

*****

I. INTRODUCTION

Ability of computer to understand human emotions and perform appropriate action is one of the key focus areas of research in Human Computer Interaction(HCI). Making computers understand human emotions will make HCI more meaningful and easier. For example, when a robot interacts with a Human, it will be able to guess the emotions and react accordingly. A psychologist can diagnose the disease easily with the help of patient's emotional state. Several researches have been done to recognize emotions using physiological signals like Electrocardiogram(ECG),Electroencephalography(EEG), Skin Temperature and also other modalities like Facial images, Gestures, Speech.

The physiological signals have proved to give accurate results for emotion detection. In this paper, recent advancements in emotion research using physiological signals is presented, making use of latest Data mining techniques for preprocessing, feature extraction and classification. The goal of this review is to study the various techniques available for the study of physiological signals to detect emotions. Section II gives brief introduction of the papers we studied.

II. LITERATURE SURVEY

For the purpose of tracking advancement in emotion detection using physiological signals, we have considered 15 papers from year 2015 and 2016. As learned from these papers, vast variety of physiological signals can be used for emotion detection, viz, Electroencephalography (EEG), Electro-cardiogram (ECG), Galvanic Skin Response (GSR), Skin temperature, Blood Volume Pressure (BVP), RESpiration (RES) and Electrodermal activity(EDA). The result is presented in tabular form, one row per paper, in descending order of their acceptance date. Analysis is done considering the type of physiological signals used, Algorithms applied, Advantages and Limitations of the approach used, Results achieved and Future scope.

Some papers mentioned here made use of standard datasets like DEAP while some papers used real time data gathering techniques using wearable sensors and non-invasive methods. The data preprocessing is done in order to remove errors. Preprocessed data is used for classification of signals, the Data mining techniques mainly used are Support Vector Machine (SVM), k-Nearest Neighbor (kNN), Naive Bayes. These techniques are used to classify the emotions based on the data acquired. Entries in few columns of the table are marked with '--', this is to indicate that the particular entry could not be found in that research paper.

Summary of reviewed research papers is as follows:

Sr. No.	Name of the paper	Month & Year	Algorithms Used	Advantages	Limitations	Result	Future Work
1	Inside the Mind of the Insider: Towards Insider Threat Detection Using Psychophysiological Signals (ACM)	Feb, 2016	Support Vector Machine classifier using k-fold cross validation	Real-time, Reveal valuable knowledge about the malicious behaviours, Effective solution for detecting insider threats	Relies on users wearing the headset in order to continuously monitor the signals, Privacy issues of monitoring bio-signals	95% accuracy	--
2	Recognition of emotions in autistic children using physiological signals (Springer)	March, 2016	RBF kernel function	Non-invasive methods used.	Reluctance on wearing the device.	90% accuracy	Real time analysis will need to be developed. Android application that harnesses the power of neural networks
3	Designing a Smart Scarf to Influence Group Members' Emotions in Ambience: Design Process and User Experience (Springer)	2016	--	Colour change of scarf depicts change of mood, helps in team work.	Sensors may cause inaccurate readings.	--	Include BVP and other signals, conduct an evaluation with high fidelity prototype
4	Recognizing Emotional States Using Physiological Devices. (Springer)	2016	--	System could recognize the emotional states with high accuracy using few number of physiological devices.	Due to the fact that it was a huge dataset, it was not possible for WEKA application to process the data of all 24 participants together.	Classification for 1] 'two-class': J48 & IBK with accuracies of 97.7584 % & 95.4684 % respectively. 2] 'six-class': J48 and IBK with accuracies of 96.5014 % & 91.9333 % respectively.	Conduct more user studies where we will use physiological data and facial expressions for recognizing these emotional states.

5	Emotion Recognition Based on Physiological Sensor Data Using Codebook Approach. (Springer)	2016	*k*-means clustering.	Effective feature extraction by codebook approach, soft assignment and feature fusion approaches useful for smoothed distribution of code-words.	Histogram-type feature used is restrictive as it only represents the distribution of pre-defined code-words, & not the variation of code-words.	Maximum recognition accuracy 54.3%.	Sophisticated feature representations can be investigated. Test the Fisher kernel approach.
6	Association Rules on Relationships Between Learner's Physiological Information and Mental States During Learning Process. (Springer)	2016	Association rules mining.	Experimental paradigms will become more convenient as EEG instruments are currently becoming less expensive and more sophisticated in function.	The rules regarding mental state of Shame, pride has much variations that its difficult to predict their existence. EEG & pulse volume excluded due to missing values.	It is possible to infer a learner's mental states from the learner's physiological information together with the teacher's speech acts if the learner's mental states are that of Enjoyment or Anxiety.	Promote the accuracy of the predicting rules by employing more types of data on teachers' speeches and behaviours & pay more attention to the changes of learners' mental states.
7	A More Complete Picture of Emotion Using Electrocardiogram and Electrodermal Activity to Complement Cognitive Data. (Springer)	2016	Naive Bayes classifier, SVM.	The Naive Bayes classifier gave higher accuracy when combining ECG and fNIRS Data.	There is a need for more research into fusion of physiological data to boost the accuracy levels.	The combination of Electrocardiogram/Electrodermal Activity and cognitive data (fNIRS) provides higher accuracy than Electrocardiogram/Electrodermal Activity alone.	Apply it to large data set as well as cross subject data.
8	Dissimilarity measure based on ordinal	January, 2016	Detrended Fluctuation Analysis, Multiscale	The implemented method can successfully	--	--	Needs further investigation, can be applied to

 ISSN: 2321-8169
16 – 21

	pattern for physiological signals (Elsevier)		Entropy Analysis.Accordingtothera nkandfrequencyofordinal patternsfortwotime series.	characterize the unique underlying pat-terns of subjects at similar physiologic states.			other physiological signals
9	Smoothening and Segmentation of ECG Signals Using Total Variation Denoising - Minimization-Majorization and Bottom-Up Approach (Elsevier)	2016	TVD-MM approach, Iterative merge	Successfully de-noised ECG signals	--	Accuracy increases with increase in number of segments	More accurate results may be obtained by proper selection of polynomials for approximation of sections. Individual sections may provide better results for TVD-MM techniques
10	Stress in interactive applications: analysis of the valence-arousal space based on physiological signals and self-reported data. (Elsevier)	24 May 2016	Incremental Stress Region Construction (ISRC) algorithm.	ISRC algorithm improves the classification accuracy.	It did not employ any feature selection techniques, which might improve the classification accuracies. Furthermore, the dataset included VA blocks with no ratings.	Classification accuracy; from 5.4 % for C-SVM to 24.9 % for KNN.	To enlarge our dataset in order to investigate the effect (if any) of gender on the identified stress region(s) in the VA space. Investigating the reported stress regions using additional physiological signals.
11	From Physiological data to Emotional States: Conducting a User Study and Comparing Machine Learning Classifiers (Sensors & Transducers)	June, 2016	Decision tree classifier(J48), k-Nearest Neighbours(IBK) classifier, WEKA.	System was able to recognize the aforementioned emotional states by using physiological devices and machine learning classifiers (i.e. J48 and IBK) with high accuracies	Physiological sensor has to be fixed properly on the participant's skin in order to predict their emotional states successfully	98% accuracy	Conduct user studies using facial expressions for recognizing emotional states

ISSN: 2321-8169
16 – 21

12	A Comparison of Physiological Signal Analysis Techniques and Classifiers for Automatic Emotional Evaluation of Audio Visual Contents (frontier in computation alneuroscience)	July 2016	Random Forest (RF) Random Forest with attribute selection (ASC) Random Forest with Multi-Class Classifier (MCC) and Bagging (BAG)	The Autonomic Nervous System is more useful for emotion classification than the Central Nervous System' is supported by.	A more comprehensive and exhaustive validation with more data could have been performed to get even more reliable results.	Random Forest using the selected attributes from the dataset combining GSR and HRV signals: 87.62% accuracy (Best accuracy)	Voting majority could be used to improve the accuracy of each class independently , which could lead to better global results
13	Short-term Analysis of Heart Rate Variability for Emotion Recognition via a Wearable ECG Device (IEEE)	2015	Time domain analysis Frequency domain analysis	--	--	50 % accuracy	More subjects will be recruited to analyse the more parameters of ECG.
14	The First Affect Recognition Challenge Bridging Across Audio, Video, and Physiological Data (ACM)	2015	A hybrid decision-fusion based on Support Vector Regression (SVR) and Neural Networks (NN)	Multimodality is a key to achieve high performance in the prediction of emotional arousal and valence from spontaneous recordings, as all modalities contribute to the prediction of emotion	--	--	--
15	Cluster Based Wireless Mobile Healthcare System for Physiological Data Monitoring (Elsevier)	December, 2015	ODAC (Online Divisive-Agglomerative Clustering), K-means algorithm, Online Distribution Resource	Best suited in healthcare domain	Attack from network failure or network congestions	96% accuracy	Risk levels alert can be sent to the expert diagnosis system.by which first aid diagnosis can be informed to the patients

			Aware (ODRA) Clustering				before physician reaches.

III. CONCLUSION

In this paper, various techniques that are used to perform data mining task on datasets consisting of physiological signals are studied. Different physiological signals and their features are explored. Various filtering and pre-processing methods applied on datasets to get a refined dataset for further processing are studied. This paper analyses results as well as advantages and limitations of existing projects and the improvements that can be made in future. It outlines the basic tasks undertaken to analyse physiological signals and detect emotions to form user profile.

IV. REFERENCES

[1] Yessir Hashem, Hassan Takabi, Mohammad GhasemiGol, and Ram Dantu, "Inside the Mind of the Insider: Towards Insider Threat Detection Using Psychophysiological Signals", The 7th ACM CCS International Workshop on Managing Insider Security Threats (MIST15), Denver, Colorado, USA, Feb 2016.

[2] Niranjana Krupa, KarthikAnantharam, Manoj Sanker, Sameer Datta,John Vijay Sagar, "Recognition of emotions in autistic children using physiological signals", IUPESM and Springer-Verlag Berlin Heidelberg, July 2016.

[3] Ali Mehmood Khan, Michael Lawo, "Recognizing Emotional States Using Physiological Devices", Springer International Publishing Switzerland 2016, 22 June 2016.

[4] KimiakiShirahama, Marcin Grzegorzek, "Emotion Recognition Based on Physiological Sensor Data Using Codebook Approach", Springer International Publishing Switzerland 2016, 26 May 2016.

[5] KazumaTakehana, TatsunoriMatsui,"Association Rules on Relationships Between Learners Physiological Information and Mental States During Learning Process", Springer International Publishing Switzerland 2016, 21 June 2016.

[6] DanushkaBandara, Stephen Song, Leanne Hirshfield, SenemVelipasalar, "A More Complete Picture of Emotion Using Electrocardiogram and Electrodermal Activity to Complement Cognitive Data", Springer International Publishing Switzerland 2016, 21 June 2016.

[7] Jing Wanga, PengjianShangb, WenbinShib, Xingran Cui, "Dissimilarity measure based on ordinal pattern for physiological signals", Elsevier, August 2016.

[8] Alexandros Liapis, Christos Katsanos, Dimitris G. Sotiropoulos, Nikos Karousos, Michalis Xenos,"Stress in interactive applications: analysis of the valence-arousal space based on physiological signals and self-reported data", International Conference on Computational Modeling and Security (CMS 2016) , 11 June 2016.

[9] Ali Mehmood Khan, Michael Lawo, 'From Physiological data to Emotional States and Transducers by IFSA Publishing, S. L., Vol. 201, Issue 6, June 2016, pp.

[10] Adrian ColomerGranero, Felix Fuentes-Hurtado, Valery Naranjo Ornedo, JaimeGuixeresProvinciale, Jose M. Ausin, and Mariano Alcaniz Raya, "A Comparisonof Physiological Signal Analysis Techniques and Classifiers for Automatic Emotional Evaluation of Audio Visual Contents", frontiers in Computational Neuroscience, 2016 Jul 15.

[11] Han Wen Guo, Yu Shun Huang, Jen ChienChien, JiannShingShieh,"Short-termAnalysis of Heart Rate Variability for Emotion Recognition via a Wearable ECGDevice", IEEE, 28-30 Nov. 2015.

[12] Sagar B. Tambe, Ravindra C. Thool, Vijaya R. Thool, "Cluster Based WirelessMobile Healthcare System for Physiological Data Monitoring", ElseVier, ProcediaComputer Science Volume 78, 2016, Pages 40-47 1st International Conference onInformation Security and Privacy 2015

[13] Chao Li, Chao Xu, Zhiyong Feng, "Analysis of physiological for emotion recognition with the IRS model", Neurocomputing Volume 178, 20 February 2016,Pages 103111 Smart Computing for Large Scale Visual Data Sensing and Processing Selected papers from the 2014 International Conference on Smart Computing(SMARTCOMP 2014)

[14] Wanhui Wen, Guangyuan Liu, Nanpu Cheng, Jie Wei, PengchaoShangguan,Wenjin Huang, "Emotion Recognition Based on Multi-Variant Correlation ofPhysiological Signals", IEEE, 04 June 2014.

[15] Baha Sen, Musa Peker, Abdullah Cavusoglu, Fatih V. Celebi, "A ComparativeStudy on Classification of Sleep Stage Based on EEG Signals Using Feature Selection and Classification Algorithms",SpringerLink, Journal of Medical SystemsMarch 2014