Exploring Wrist Pulse Signals using Empirical Mode Decomposition: Emotions

Nidhi Garg, Arvind and Gurpreet Kaur

Department of Electronics and Communication Engineering, University Institute of Engineering and Technology, Panjab University, Sector 25, Chandigarh 160025, India

nidhi_garg@pu.ac.in

Abstract. Emotion recognition is attracting considerable interest among the research community. In this work, Empirical Mode Decomposition has been implemented to derive both statistical and nonlinear features from Wrist Pulse Signal to classifying emotions namely anxiety and boredom. Wrist Pulse signals were extracted from 24 subjects using TETRIS game as a stimulus using Fission and Fusion approach. The acquired signals were pre-processed to remove unwanted noise and artefacts present within the signal. In addition, various classifiers namely Naive Byes, Support Vector Machine, K-Nearest Neighbour, Logistic Regression, Linear Discriminant Analysis, Quadratic Discriminant Analysis were considered. Results from these classifiers indicate that both Logistic Regression and Quadratic Discriminant Analysis gave an indistinguishable accuracy of 99.71% (fiss) and 77.08% (fusion) for anxiety state. Moreover, for boredom state, the highest classification accuracy was 66.67 % for Naive Bayes using fission and 64.58% for fusion. Results highlight the impact of empirical mode decomposition with hilbert transform for the recognition of emotion from wrist pulse signals.

Keywords—Empirical Mode Decomposition, Fission, Fusion, Hilbert Transform, Intrinsic Mode Functions, Physiological Signals, Wrist Pulse Signal

1. Introduction

Emotions are feelings that influence the human body as well as mind. The communication with the surrounding environment is accomplished with the assistance of emotions. A plausible explanation was given on how emotions supersede, emerge and wane according to set of laws [1]. Emotion recognition is a vast field and has several applications. The applications are disseminated across distinct fields such as medicine, e-learning, marketing and entertainment. In the healthcare, human emotions are pertinent for the diagnosis of diseases along with knowledge of patient emotional state [2]. The researchers all over the world are focusing on the robust emotion recognition system for the efficient recognition of human emotions. The emotion recognition approaches encompass facial, gesture, posture, speech and physiological signals. Facial, gesture, posture, voice suffered from masking. This impediment lays a foundation of physiological signals those are governed by the Autonomous Nervous System (ANS). Physiological signal involves Electrocardiogram (ECG) [3] [4] [5] [6] [7] [8] [9], Electromyogram (EMG) [4] [10] [11] [12] [13], Electroencephalogram (EEG) [4] [14][15], Skin Conductance (SC) [4] [5] [13], Skin Temperature (SKT) [4] [6] [13], Photoplethysmography (PPG) [4] [6] [13], Galvanic Skin Response (GSR) [4], Respiration Pattern [4] [5] [12] [13] and Wrist Pulse Signal (WPS) [16] [17] [18] [19] [20] [21] [22]. ECG, EMG, EEG gives limited information about the human system like ECG-cardiovascular, EMG-muscular, EEG-brain

Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

Published under licence by IOP Publishing Ltd
activity but on the other hand WPS gives information about the organs and cardiovascular system. WPS has its roots in Ayurveda and any changes in body can be analysed through radial artery of a wrist of human body and these signals are known as wrist pulse signal (WPS). The heart has set of muscles which on contraction and expansion produces wave. This can be enumerated from the radial artery of wrist using the distinct pressure sensors. WPS have been acquired from wrist noninvasively using three fingers index, middle, ring finger (Vata, Pitt, Kaph). Now, due to development in technological environment WPS acquisition and analysis transforming into a computerized approach. Additionally, it minimizes the utilization of costly diagnostic test and help in the diagnosis of almost all types of diseases. Moreover, the placement of electrode is vital for the proper emotion recognition. The number of electrodes and placement is very complex in case of ECG, EMG, and EEG but for WPS one to three pressure sensor on radial artery of wrist is required to be positioned.

Consequently, WPS has been chosen to be explored for the emotion. In this study, focus is given on WPS analysis for anxiety and boredom emotion. Considering the inferences from the related study as mentioned in Section II, rigorous efforts have been made to accomplish the objectives : 1) to study EMD, Hilbert transform and DFT techniques for emotion recognition using WPS, 2) to extract various statistical and non-linear features for anxiety, boredom and reference state and 3) to compare different techniques and classifiers for WPS anxiety, boredom and reference state.

Distinct sections are discussed as follows: Section II- gives insight to previous work done by researchers in the field of emotions. Section III- discussed material and methods of emotion elicitation protocols, data acquisition, pre-processing, feature extraction and classification. Section IV- highlights the results and discussions and finally in Section V- conclusions.

2. Related works
Various researchers are working in the field of emotion recognition using physiological signals. The number of subjects, stimuli method, types of emotions, feature extraction techniques and classification rate vary from researcher to researcher. Many emotion features for different physiological signals have been extracted with Hilbert Huang Transform (HHT) in frequency domain from each Intrinsic Mode Functions (IMFs) using Empirical Mode Decomposition (EMD). Researchers used EMD on ECG, EEG and other physiological signals and features were extracted using fission (individual IMFs) and fusion (combination of IMFs) approaches. ECG and EMG have also been computed for emotions with Hurst and Higher Order Statistics (HOS) features using Rescaled Range Statistics (RRS) and Finite Variance Scaling (FVS). Some researchers focussed on comparing of EMD, EMD with Hilbert transform, EMD with Discrete Fourier Transform (DCT). Stimuli also played a key mantle in the field of emotion recognition. Different stimuli for elicitation are used in past to unravel distinct ways of emotion elicitation. Table 1 shows comparison of distinct physiological signals for emotion recognition and listing type of bio-signal, emotion/s, stimuli, feature extraction and achieved classification rate.

| Ref No. | Bio Signal      | Emotions          | Stimuli         | Feature extraction       | Classification and Accuracy (%) |
|---------|-----------------|-------------------|-----------------|--------------------------|--------------------------------|
| [5]     | ECG, EMG, SC, RSP | joy, anger, sadness, pleasure | music            | EMD, HHT                 | SVM fission -76% fusion and fission approaches-71% |
| [6]     | ECG, EDA, SKT, PPG | Boredom, Pain, Surprise | Audio          | Heart rate, Heart rate variability, Ratio of low to high frequency power | DFT- 84.7, LDA-74.9, SVM-62, CART-67.8, Naïve Bayes- 71.9 |
[7] EEG \quad \text{sad} \quad \text{sad pictures} \quad \text{EMD with Wavelet domain, time, frequency and non-linear methods} \quad 82.43\% - \text{nonlinear features}, 73.33\% - \text{Db4 wavelet measures}, 64.29\% - \text{time and frequency} \\
[9] ECG \quad \text{Basic emotions except anger} \quad \text{Audio, Visual} \quad \text{Rescale Range Statistics, Finite Variance Scaling, Higher order Statistics (Hurst, Skewness, Kurtosis)} \quad \text{Finite Variance scaling and Higher order statistics 92.87 (random)} \\
[12] EEG, ECG and RESP \quad \text{positive, neutral and negative} \quad \text{Video} \quad \text{EMD, HHT-Percentage power spectral density} \quad \text{SVM-72.5\%} \\
[13] BVP, EMD, SC, SKT, RESP \quad \text{Six basic emotions} \quad \text{pictures} \quad \text{Statistical features} \quad \text{Fisher discriminant, SVM 92} \\
[15] ECG \quad \text{active arousal and passive arousal/valence} \quad \text{Pictures and video game} \quad \text{EMD, HHT} \quad 89\% \\
[19] ECG \quad \text{happiness, sadness, fear, surprise and disgust} \quad \text{video clips} \quad \text{EMD, HHT, DFT} \quad \text{KNN- 48.53} \quad \text{LDA- 52.11 (user independent)} \\
[21] EEG \quad \text{Happy, Calm, Sad, Fear} \quad \text{Video} \quad \text{EMD-ApEn First four IMFs used} \quad \text{Deep Belief Network and SVM -83.34\%} \\
[22] ECG \quad \text{joy, anger, sad and pleasure} \quad \text{EMD, HHT, DFT} \quad \text{Multi discriminant analysis and K-NN} \\
[23] ECG \quad \text{Joy, anger, Sadness, Pleasure} \quad \text{Music} \quad \text{Db5 Multi scale wavelet decomposition} \quad \text{Neural Network, 91.67 (RBF), 87.5 (BP)} \\
[24] ECG \quad \text{Pleasure, Anger, Joy, Sad} \quad \text{Color (Four)} \quad \text{Poincare plot ANOVA} \quad \text{IF THEN Rules 95.71} \\
[25] ECG \quad \text{sad, joy, tension, peace, valence, arousal} \quad \text{Music} \quad \text{SFFS-KBCS-based, GDA} \quad \text{LV-SVM-61.52\% Valence-82.78\% arousal-72.91\%} \\

Note:
CART: Classification and Regression Tree  
ECG: Electro Cardio Gram  
EMG: Electro Myo Gram  
EEG: Electro Encephalon Gram  
EDA: Electro Dermal Activity  
GSR: Galvanic Skin Response  
KNN: K nearest Neighbor  
LDA: Linear Discriminant Analysis  
SC: Skin Conductance  
SKT: Skin Temperature  
SVM: Support Vector Machine  
RESP: Respiration  
ApEn: Approximation Entropy  
Poincare plot  
BVP: Blood Volume pulse 
IAPS: International Affective Picture System  
LV-SVM: Least squares support vector machine  
SFFS-KBCS: forward floating selection-kernel-based class separability  
GDA: generalized discriminant analysis
Table 1 clearly shows that emotion recognition field have been explored in depth and unfolded by the researchers using the distinct physiological signals. Manifold features extraction techniques like EMD, Hilbert Transform, RRS, FVS, HOS, DFT, and wavelet transform were utilized by researchers to extract various features. Additionally, classification rate was mainly used to recognise the performance of system. Overall, previous work in the field of emotion recognition acts as a motivation for further research. It has been considered that HHT, EMD techniques are most popularly used for emotion detection. Consequently, WPS have been explored for the emotions just like other physiological signal in this research work. So, further discussion is followed by the materials and methods, type of techniques- HHT, EMD, DFT and classifiers that have been used to detect emotion from WPS.

3. MATERIAL AND METHODS

3.1 Emotion Elicitation Procedure

The gateway to start the research process is use of emotion elicitation procedure. This entails a method to elicit the emotions. Two emotions boredom, anxiety along with reference state are considered. Physiological signals cannot be masked externally so there exists an emotion elicitation procedure to elicit emotions. This encompass pictures of International Affective Picture system (IAPS), music, audio and audio video etc. The intensity of emotions induced varies among the subjects and rely on social and psychological factors. Figure 1 represents that TETRIS game is being used to elicit emotions in this study. There are distinct levels of the game. Levels are set according to elicitation of emotions. The players can freely select the levels of game according to their discretion. Boredom is induced at lower level (level 1 or 2) when played for longer duration. While Anxiety is induced using the higher levels (level 8 or 9). Before acquisition of physiological signals, the subjects were introduced with the rules of the game.

![Emotion Elicitation and Data Acquisition Process]

Figure 1: Emotion elicitation in WPS

3.2 Data Acquisition and Pre-Processing
Further, data acquisition is carried by set of pressure sensors and DAQ card PCI 6251. The sampling frequency of 250 Hz is considered for acquisition of WPS. WPS have been collected using Electronics Pulse Analyzer [18] from healthy subjects after taking consent. Twenty-four subjects participated in the process and wrist signals for reference, anxiety and boredom states were acquired only from Vata location of left hand of individuals for further analysis.

Figure 2: Methodology

Figure 2 represents all steps need to clean a signal prior feature extraction. Pre-processing is pertinent in the examination of physiological signals. During signal acquisition, signal is affected by noise or outliers which degrade the quality of signals. These artefacts should be removed to get accurate physiological signal analysis. The rationale behind these artefacts is the baseline wander, power-line noise, subject movement, wrongly placed electrodes. Our previously published work [17] has been put into practice for pre-processing of reference, anxiety, boredom states of WPS. Power-line interference was removed by using Notch filter. A 4th order band-pass filter with suitable range of 0.05-15Hz was used to remove the higher frequency components. Wavelet function db9 with 9 levels was used to remove the baseline wander. The pre-processed signal is not of equivalent length due to lot of variations. Normalization and segmentation elucidate the problem by extracting the signal in a single period. The signal is further segmented, and the resulting signal is freed from noise and ready for features extraction. Furthermore, outlier segments are removed using C-DDTW

In this research work, features of emotional WPS has been extracted in three different cases i.e. EMD (case1), EMD + Hilbert (case2), EMD + DFT (case3). Furthermore, these three cases pass through two distinct approaches (fission and fusion) for analysis of emotion states obtained from WPS. In the fission approach, each of 9 IMFs was utilized individually for feature extraction and further used for classification to list out the most prominent IMFs. In the second approach, fusion of IMFs of interest was executed to foster an alternate approach in contrast to first one.

3.3 Feature Extraction and Classification

Empirical Mode Decomposition (EMD) including Hilbert Huang Transform (HHT) and Discrete Fourier Transform (DFT) have been used to extract the features from the WPS.

3.3.1 Empirical mode decomposition
EMD is decomposition of non-linear and non-stationary time series into amplitude-modulated and frequency-modulated waveforms. EMD decomposes the WPS signal into the finite number of Intrinsic Mode Functions (IMFs). The faster IMFs are extracted first. This means as level of IMFs number increases, the oscillatory nature of IMFs becomes weaker. It certainly agrees to the causal trend of the signal. In this work, nine IMFs has extracted using the EMD method. There are certain conditions which need to be satisfied for the generation of IMFs. The conditions are as follows.

a) The number of maxima and minima and number of zero crossing should be equal or differ by one.
b) The mean value due to local maxima and minima should be zero.

Additionally, every IMF should follow a sifting process. An iterative algorithm for the extraction of IMFs is discussed in Figure 3.

![Figure 3: Iterative algorithm for the extraction of IMFs](image)

The r_n (t) should be a monotonous function to end the sifting process.

\[ x(t) = \sum_{p=1}^{n} c_p(t) \]

The stopping criterion is pertinent for the number of IMFs to be estimated in the research process. The algorithm ends when the value of standard deviation is between 0.2 and 0.3 [8]. Predominately, standard deviation is in prevalence these days among the researchers [8] for this purpose.

\[ SD = \frac{|c_{k-1} - c_k|^2}{c_{k-1}^2} \]

Where \( C_k \) is the components of shifting and number of shifting taking place when extracting an IMF from WPS is represented by k.
3.3.2 Hilbert Transform

Hilbert Huang Transform (HHT) is another technique utilized for the examination of non-stationary signals in this research work. IMFs obtained do not convey anything directly at all. These IMFs components should be transformed into frequency domain. This is accomplished using HHT and it is applied on each of the IMFs to get the desired result. So, here IMFs components transformed into frequency domain.

Hilbert transform is calculated as [13]:

\[ H(x(t)) = \frac{1}{\pi} Q \int_{-\infty}^{\infty} \frac{x(t)}{t-t'} dt' \]

Where Q indicates the Cauchy principle value, x(t') is the WPS signal, t' is any particular time instant, dt' is the small change in the value of time, t - t' is the difference in the time instants. HHT is applied on each of the IMFs to get the desired result. The algorithm used here is lacking mathematical interpretation and used the certain iterative steps to compute the output.

\[ Y(t) = x(t) + jH(x(t)) \]

Where the x (t) and H (x (t)) represents the real and imaginary part respectively.

HHT is used to compute the instantaneous amplitude and frequency respectively. For this purpose, the calculation of derivative of frequency is accomplished.

\[ A(t) = \text{abs} (Y(x(t))) \]

\[ f(t) = \frac{1}{2\pi} \frac{d\theta(t)}{dt} \]

3.3.3 Discrete Fourier Transform

Discrete Fourier Transform (DFT) is an algorithm used for the transformation of signal from time domain to frequency domain. It gives no idea about the local properties such as instantaneous frequency and amplitude. Rather, it provides the frequency content of whole signal. There are restrictions of Linear time invariant (LTI) system. Due to this, it become unsuitable for the non-linear and non-stationary signal [23]. This work is utilized to calculate the frequency content of the complete IMF; we employed DFT to the various IMFs obtained because of EMD.

Discrete Fourier Transform is calculated as [13]

\[ X(k) = \sum_{j=1}^{N} x(j) \omega_N^{(j-1)(k-1)} \]

Where \( \omega_N = e^{-2\pi i/N} \)

Where x is the input WPS in the time domain, X is the WPS in the frequency domain and N is the total number of samples, k varies from 0 to N-1, j varies from 1 to N, j and k are instants to show the variation in the DFT.

Feature extraction is one of the main process in signal processing. There are distinct types of features extracted by researchers - time, frequency, wavelet, statistical and nonlinear features. Prior researchers not paid much heed to nonlinear features. In this study, nonlinear and statistical both used for feature extraction. Hurst, Entropy, Skewness, Kurtosis, Mean Instantaneous frequency, Mean, Standard Deviation, Minimum, Maximum and Power in all total of 10 features have been extracted and
calculated from IMFs of the WPS under three emotions (anxiety, boredom, reference) with fission and fusion approaches. A comparative study is carried out among the EMD, EMD + Hilbert and EMD + DFT techniques using fission and fusion approaches for our database.

After the non-linear and statistical features extraction, the next task is to classify emotions using various classifiers. The input to the classifiers is extracted features and whole dataset is divided into training and testing. There are several machine learning algorithms being used in the previous studies. Classification is an exemplar of supervised learning which is used to find the sub-categories from the testing data. The selection of classifiers is arduous task due to the distinct nature of signals. This work have employed Naive Bayes, SVM [5], [24], [4], [25], KNN (n=1 and 7) [10], Logistic Regression, decision table, LDA [26], QDA as the classifiers. In addition, a 10-fold cross validation technique was used to evaluate the classification rate. Here, the seven classifiers are used for the successful comparison of classification.

4 Results and Discussions

EMD has been employed on all the pre-processed signal of different emotional states which gives rise in IMFs. Figure 4 represents decomposition of anxiety state WPS of subject 1 using EMD technique. There are ample approaches for the selection of efficacious IMFs. Here, first nine most favourable IMFs are taken into consideration based on stopping criteria. Various features as discussed in Section III were extracted from 9 IMFs of EMD. Furthermore, EMD has been combined with the Hilbert and DFT. So, features were also extracted after applying EMD + Hilbert and EMD + DFT. In addition, in fission approach, each of 9 IMFs was employed for feature extraction. Further, the favourable selection of IMFs is important for proficient results therefore the most prominent IMF for each technique in relation to emotional state were identified. Similarly, in fusion approach, prominent IMFs were combined to extract features. Motive to do this study was to find best technique to assess emotions from WPS so the comparative analysis was carried out using distinct classifiers by considering the main and foremost factor i.e. accuracy. Instead of representing bar graphs for all the techniques with 2 different approaches here, Figure 5 and Figure 6 shows the classification accuracy with fission and fusion strategies respectively in case of EMD + Hilbert (case2) for the different states.
Figure 4: Decomposition of WPS (Anxiety state) into IMFs
Figure 5: Comparison of IMFs using distinct classifiers with EMD + Hilbert Technique (Anxiety vs. Reference)

Figure 6: Comparison of IMFs using distinct classifiers with EMD + Hilbert Technique (Boredom vs. Reference)

An experimental result demonstrates that EMD + Hilbert gave better results than other 2 cases for our database. Figure 5 and 6 shows the role of each IMFs with distinct classifiers in anxiety and boredom state respectively for case 2 i.e. EMD + Hilbert. The analysis of complete study was accomplished using various classifiers. It has been discovered with reference to anxiety, IMF2, IMF3, IMF4, and IMF6 achieved analogous results in term of accuracy. However, the highest accuracy of 97.91% in anxiety state was achieved for logistic regression and QDA for IMF5. Therefore, IMF5 is prominent IMF in the fission process for A vs. R. While for boredom state IMF1, IMF2, IMF5 obtained the comparable performance. Additionally, for boredom state, the highest classification accuracy 66.67% was attained for Naive Bayes in case of IMF4. Here, decision table and KNN (n=7) results in the worst performance among the distinct classifiers when espoused for the classification.

Table 2 depicts the highest classification rate achieved in fission and fusion approaches for A vs. R, B vs. R, A vs. B vs. R with best classifiers. The highest accuracy after fusion of prominent IMF’s
achieved was 77.08% for Logistic regression and QDA for anxiety state. While for boredom state accuracy of 64.59% was noticed using Naïve bayes. Overall, the comparison between anxiety and boredom reveals that anxiety state classification outsmarted the boredom state. Moreover, the results quantify that efficient performance has been attained with the use of essential IMFs component/s and fusion strategies. Prior works accomplished by Jain et al [23] was focussed on the EMD, HHT and DFT. They applied these techniques to the intrinsic mode functions (IMFs). Moreover, their central focus was on the totally on the statistical and spectral features. So, the experiment results infer that the method based on EMD strategy is suitable for emotion recognition from WPS signals.

Table 2: Comparison of Emotions using EMD, EMD + Hilbert, EMD + DFT techniques with Fission and Fusion approaches using Accuracy, dominant IMFs, Classifiers.

| Emotions       | Approaches\Techniques | Fission | Fission Dominant IMF | Fusion | Fusion IMF’s | Fission Classifiers | Fusion Classifiers |
|----------------|------------------------|---------|----------------------|--------|--------------|---------------------|-------------------|
| A vs. R        | EMD                    | 52.08   | 2                    | 45.83  | 1,2          | LDA, QDA            | Decision Table    |
|                | EMD + Hilbert          | 97.91   | 5                    | 77.08  | 5            | Logistic Regression, QDA | Logistic Regression, QDA |
|                | EMD + DFT              | 54.16   | 2                    | 54.16  | 2,3,4,6,7    | Naïve Bayes         | Naïve Bayes       |
| B vs. R        | EMD                    | 70.83   | 4                    | 50     | 1,4          | Naïve Bayes         | Naïve Bayes       |
|                | EMD + Hilbert          | 66.67   | 4                    | 64.59  | 3,4,6,7,8    | Naïve Bayes         | Naïve Bayes       |
|                | EMD + DFT              | 60.42   | 4                    | 58.33  | 1,2,3,4,5,6,8,9 | Naïve Bayes         | Naïve Bayes       |
| A vs. B vs. R  | EMD                    | 41.67   |                      | 30.55  | 1,7          | Logistic Regression | Naïve Bayes       |
|                | EMD + Hilbert          | 69.4    | 5                    | 61.11  | 5            | QDA                 | Naïve Bayes, QDA  |
|                | EMD + DFT              | 40.27   |                      | 38.89  | 1,2,3,4,5,6,7 | Naïve Bayes         | Naïve Bayes       |
Results demonstrate that classification accuracy of 97.91% and 77.083% for the proposed work articulates that EMD along with Hilbert transform performed effectively with regards to Logistic Regression, QDA, Naive Bayes for the successful emotion recognition. Although prior works considered a greater number of emotions and the number of subjects yet lacks the accuracy. The proposed work had taken into consideration EMD, EMD+Hilbert and EMD+DFT in fission and fusion approach. Furthermore, results illustrated in Figure 7 and Figure 8 concluded that EMD+Hilbert outperformed in fission as well as fusion approach while comparing case1, case2 and case3 which will revitalise the field of WPS.

5 Conclusions
In this paper, WPS was examined to comprehend the emotions. Emotions recognition using EMD and Hilbert transform have been proposed for WPS. This decomposition approach being used here is a contemporary approach which decomposes the signal adaptively. The results of individual nine IMF components (fission) and in combination (fusion) have been inquired from the in-depth analysis of WPS. IMF 4 and IMF 5 play a pivotal role in the recognition of boredom and anxiety respectively during the analysis of dataset. Eventually, proposed method yields high classification accuracy as compared to the prior methods although only two emotional states were evaluated. This current
research is envisaged to yield substantial headway in the interaction of human computer interface. The greater number of subjects, emotions can be future scope in this field.

References

[1] Frijda N H 1988 The Laws of Emotion American Psychologist vol 43 pp 349–58
[2] Kwon D S, Yoon K K, Park J C, Myung J C, Jee E S, Park K S, Kim H R, Kim Y M, Park J C, Eun H K, Kyung H H, Min H J, Hui S L, Jeong W P, Su H J, Park S Y and Lee K W 2007 Emotion interaction system for a service robot Proceedings - IEEE International Workshop on Robot and Human Interactive Communication
[3] Jerritta S, Murugappan M, Wan K and Yaacob S 2012 Emotion recognition from electrocardiogram signals using Hilbert Huang Transform 2012 IEEE Conference on Sustainable Utilization and Development in Engineering and Technology (STUDENT) (IEEE) pp 82–6
[4] Jang E-H, Park B-J, Park M-S, Kim S-H and Sohn J-H 2015 Analysis of physiological signals for recognition of boredom, pain, and surprise emotions J. Physiol. Anthropol. 34 25
[5] Zong C and Chetouani M 2009 Hilbert-Huang transform based physiological signals analysis for emotion recognition 2009 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT) (IEEE) pp 334–9
[6] Goshvartous A, Abbasi A and Goshvartous A 2017 Do men and women have different ECG responses to sad pictures? Biomed. Signal Process. Control 38 67–73
[7] Agrafioti F, Hatzinakos D and Anderson A K 2012 ECG Pattern Analysis for Emotion Detection IEEE Trans. Affect. Comput. 3 102–15
[8] S J, Murugappan M, Wan K and Yaacob S 2014 Electrocardiogram-based emotion recognition system using empirical mode decomposition and discrete Fourier transform Expert Syst. 31 110–20
[9] Minhad K N, Ali S H M and Reaz M B I 2017 Happy-anger emotions classifications from electrocardiogram signal for automobile driving safety and awareness J. Transp. Heal. 7 75–89
[10] Selvaraj J, Murugappan M, Wan K and Yaacob S 2013 Classification of emotional states from electrocardiogram signals: a non-linear approach based on hurst Biomed. Eng. Online 12 44
[11] Chen Y, Yang Z and Wang J 2015 Eyebrow emotional expression recognition using surface EMG signals Neurocomputing 168 871–9
[12] Xie H and Wang Z 2006 Mean frequency derived via Hilbert-Huang transform with application to fatigue EMG signal analysis Comput. Methods Programs Biomed. 82 114–20
[13] Jerritta S, Murugappan M, Wan K and Yaacob S 2014 Emotion recognition from facial EMG signals using higher order statistics and principal component analysis J. Chinese Inst. Eng. 37 385–94
[14] Zhuang N, Zeng Y, Tong L, Zhang C, Zhang H and Yan B 2017 Emotion Recognition from EEG Signals Using Multidimensional Information in EMD Domain Biomed. Res. Int. 2017 1–9
[15] Liu X, Wang Q, Liu D, Wang Y, Zhang Y, Bai O and Sun J 2018 Human emotion classification based on multiple physiological signals by wearable system ed C Gómez, S P Schwarzacher and H Zhou Technol. Heal. Care 26 459–69
[16] Wang D, Zhang D and Lu G 2016 A robust signal preprocessing framework for wrist pulse analysis Biomed. Signal Process. Control 23 62–75
[17] Garg N, Ryait H S, Kumar A and Bisht A 2017 An effective method to identify various factors for denoising wrist pulse signal using wavelet denoising algorithm Biomed. Mater. Eng. 29 53–65
[18] Garg N, Bisht A, Ryait H S and Kumar A 2018 Identification of motion outliers in wrist pulse signal Comput. Electr. Eng. 67 776–90
[19] Rangaprakash D and Narayana Dutt D 2014 Analysis of wrist pulse signals using spatial
features in time domain 2014 International Conference on Communication and Signal Processing (IEEE) pp 345–8

[20] Rangaparaksh D and Narayana Dutt D 2015 Study of wrist pulse signals using time domain spatial features Comput. Electr. Eng. 45 100–7

[21] Srinivasulu B 2013 International Journal of Ayurveda and Pharma Research CLINICAL ASSESSMENT OF HYPOTHYROID SYMPTOMS IN DIFFERENT TYPES OF I 17–23

[22] Mills P J, Tara C, Wilson K L, Pung M A, Patel S, Weiss L, Kshirsagar S G and Tanzi R E 2018 Journal of Ayurveda and Integrative Medicine Relationships among classifications of ayurvedic medicine diagnostics for imbalances ( vikruti ) and western measures of psychological states : An exploratory study J. Ayurveda Integr. Med. 1–5

[23] Jain M, Saini S and Kant V 2017 A hybrid approach to emotion recognition system using multi-discriminant analysis & k-nearest neighbour 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI) vol 2017-Janua (IEEE) pp 2251–6

[24] Li Q, Yang Z, Liu S, Dai Z and Liu Y 2015 The Study of Emotion Recognition from Physiological Signals Seventh Int. Conf. Adv. Comput. Intell. 378–82

[25] Gouizi K, Maaoui C and Bereksi Reguig F 2014 Negative emotion detection using EMG signal Control. Decis. Inf. Technol. (CoDIT), 2014 Int. Conf. 690–5

[26] Selvaraj J, Wan K and Yaacob S 2012 Emotion Recognition from Electrocardiogram Signals using Hilbert Huang Transform