Journal of Discrete Mathematical Sciences & Cryptography
ISSN 0972-0529 (Print), ISSN 2169-0065 (Online)
Vol. 24 (2021), No. 8, pp. 2171–2180
DOI : 10.1080/09720529.2021.2009191

Early detection of mental disorder signs using photoplethysmogram : A review

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Abstract

Mental disorder is defined as psychological disorders that involve instabilities in brain function. This paper aims to provide an overview of photoplethysmogram (PPG) for detecting early symptoms of mental disorders encompassing physiology using different stimuli. This paper discusses mental disorder studies that have been highlighted in the previous literature. The contribution of the PPG is summarized through feature extraction and its accuracy classified using machine learning. Moreover, research challenges and recommendations in the field are discussed. In conclusion, there were significant changes against the early signs of mental disorders through emotional and stress levels from PPG signal morphology.

Subject Classification: *68T99.*

Keywords: *Mental disorder, Emotion, Stress, Photoplethysmogram, Feature extraction, Classification, Machine learning.*

1. Introduction

According to statistics in 2017, approximately 792 million people worldwide suffer from mental disorders (MD), and one in ten people are affected by substance abuse[1]. The World Health Organization (WHO)

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reported that 10 to 20% of children and adults experience MD. MD includes many different illnesses, with depression being the most prominent [2]. MD is also closely related to mental health influenced by emotions, such as stress, depression, and anxiety [3]. Early detection of MD is important to prevent the worsening condition of a person despite the difficulty in detection [4]. The early detection of MD has been shown to reduce the number of subsequent consultations, shorten the duration of an episode, and result in far less social impairment in the long term [5]. Currently, the status of mental health can be assessed using self-report questionnaires[6] and online survey [7], the questionnaires are designed to detect specific patterns of feelings or social experiences. Most low-income countries are facing problems in providing mental health care due to a lack of resources thus the patient failing to receive proper treatment [8]. The studies on mental health detection using bio-signal methods have increasingly emerged. This mature approach becomes a reliable and sufficiently useful application to improve one's quality of life significantly [9]. Physiological data can be explored using this method to produce a simple, accurate, and reliable test to monitor mental state in the early stages [10]. The relevant matters regarding PPG studied in the early detection of MD in previous studies are reviewed in this paper. Challenges and recommendations for future work are also included. Finally, the conclusions are given.

2. Mental Disorder Concepts

The American Psychiatric Association states that nearly 300 MD [11] with a broad variety list of symptoms are listed in the Diagnostic and Statistical Manual of MD (DSM-5). Some of the main groups of MD listed in [12] are mood disorders, anxiety disorders, personality disorders, psychotic disorders eating disorders, trauma-related disorders and substance abuse disorders. These problems also affect the emotions, thoughts, and behaviors of an individual. The study in [13] mentioned a high prevalence of MD involving mood dysfunction, namely, emotional, mood, and anxiety disorders. In the study [14], identifying the disease is difficult because it depends on the specific disorder, the circumstances of an individual, and other environmental factors. However, some warning signs of a person who needs help may include excessive anxiety, prolonged depression and apathy, thinking or talking about suicide or self-harm, extreme mood swings, anger, hostility, or excessive violent behavior [15]. Thus, most of the previous studies are focused on indicators, such as emotion, stress, anxiety, and depression, as possible early signs of mental health problems [16] .

3. Photoplethysmography (PPG)

This review will focus on the physiological signal which is closely related to heart rate and blood pressure using PPG [17]. Study [18] presented that bio-signals can be measured by autonomic nervous system (ANS) reactions which conclude cognitive load can affect heart function and is simultaneously associated with the changes. The ANS controls body phenomena and acts unconsciously by regulating bodily functions, such as changes in temperature, respiratory rate, and heart rate [19]. It also contains the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). These systems reflect the reaction of the 'fight or fly' situation and also calm the body down [20]. PPG is a non-invasive technique for measuring changes in blood volume due to the blood pulsatile nature of microvascular tissue under the skin [21]. The PPG signal is measured from the finger using an infrared light sensor to sense the rate of blood flow [22]. PPG transmission waveform has the following two components: alternating current (AC) and direct current (DC). The study [23] showed the AC component is caused by the changes in blood volume with each heartbeat (between the systolic and diastolic phases of the cardiac cycle), and the DC component changes slowly with respiration and is associated with SNS activity and thermoregulation[24]. The PPG signal can provide valuable information regarding cardiovascular, respiratory systems in a simple technique compared to the electrocardiogram (ECG) [25]. It does not require the attachment of electrodes to a patient's body. The study [26], found a significant correlation between pulse rate from PPG and heart rate as well as heart rate variability (HRV) from ECG. However, the researchers also determined that ECG was more accurate for HRV detection rather than PPG.

3.1 *Feature Extraction & Classification*

The PPG waveform and its first derivative comprise three peaks and valleys, systolic peak, dicrotic notch, and diastolic peak [27]. This information can be obtained if the feature point has been identified from the PPG pulse wave in advance. The authors in the article presented that the position of the notch and diastolic peak in the PPG wave is unclear due to several factors, such as the effects of aging. Therefore, PPG derivatives are used in determining the position of the point, second derivative (SDPPG) waveform. Another feature provides different information from PPG, such as area ratio, delta time, peak time, area time, amplitude, the area under the curve, and valley or peak [28]. The raw PRV gave better results than its second derivative, but it depends on the subject and measurement specification [29]. The HRV is able to estimate the emotional aspects of a subject in addition to physical characteristics using PPG signal [30]. Study [31] applied the differences of PPG morphological features and feature time series in the study of emotion recognition. The PPG signals were filtered and showed significant differences ($p < 0.05$) using statistical analysis. Such an application determined that temporal features such as time intervals between $onset_i$ to $peak_i$ were more sensitive in responding to emotion changes than area and amplitude features. The study suggested that the frequency domain is more suitable for short-term 5-minute time series analysis. Nevertheless, this study requires more data in the future and involves more types of emotions to confirm the practical clinical application of the conclusions obtained. The time from pulse onset to peak and the time from the dicrotic notch to pulse end have been identified potentially in the assessment of mental stress [32]. These features have been detected by various fiducial points through the first, second, and third derivatives of a PPG waveform. The study presented that the characteristics change significantly and the strength of significant trends has been quantified by statistical analysis. Another study [33], applied the combination of skin temperature, ECG, and PPG to measure acute stress. The temperature ratio, mean heart rate, pulse wave rising time, pulse transit time, and pulse width until reflected wave were obtained as informative features. The stress estimation function (S_{est}) has been used to assume a linear relationship between the selected features and stress levels. The difference between rest and stress conditions was modest in the range of 18% but it is considered as a significant for stress effect.

In feature extraction, the signal will be filtered to remove noise or artifacts for reliability on the classification process [31]–[33]. In the emotion recognition study [34], the researchers used the attributes of HR and HRV from PPG signal. This study discovered nineteen features (time and frequency domain) derived from 150 healthy subjects and obtained 91.8% using linear discriminant analysis (LDA) technique compared to other algorithm such as decision tree (DT), and support vector machine (SVM). The classification of stress study [35], used PRV derived from 35 healthy subjects to achieve different results from different algorithms. The average classification accuracies achieved by random forest (RF), SVM and logistic regression (LR) were 91%, 88%, 100%, and 86%, 67%, 100%, and 82%, 78%, 100% for the accuracy, specificity and sensitivity, respectively. The authors suggest that random forest (RF) is better in handling noise and advance in data pre-processing than other ML. By contrast, the study [36], record the heart rate using Geneva affective picture database to predict the mental stress condition. The study demonstrates that the SVM achieved the best accuracy using the polynomial kernel, 82% in training and 62% percent in testing.

4. Discussion and Conclusion

This paper aims to provide an overview of potential PPG for detecting early signs of MD encompassing physiology. MD generally comprises stress, emotions, mood disorders and others. PPG is the only bio-signals that uses a light sensor device while others use an electrical activity approach. Considering mobility, using PPG as a measurement tool is easy and less burdensome for participants, the monitoring process can also be done wirelessly based on the study [37]. However, PPG also has weaknesses considering the relatively low resistance to noise, and its signal can be easily disturbed compared to other bio signals [38], [39]. For the study of MD, the position of the sensor or device should consider the comfort of the participant and the appropriateness of the calibrated state of stimuli. Therefore, performing experiments on MD is quite difficult in real life due to the sensitivity level of the device to conciliation with interference or noise whether derived from the environment, motion and artifacts. Obtaining PPG signals that are free from noise is remarkably challenging [40]. The PPG features such as time domain, frequency domain and PPG morphology can be used in the development of predictive models in the early detection of mental problems. As suggested in a study [41], initial screening was performed to obtain optimal signal quality before the feature extraction process. In addition, the filtering process is recommended to be done automatically and manually to improve the quality and reliability of the signal obtained. Based on previous studies, comparisons were made against several algorithms. It is found that, the classification of features extracted from PPG signal using ML has the potential to achieve accuracy of 80% and above. In the study [42], stated that the accuracy of the classifier is depends on the quality of data and each ML model's accuracy may varies with different data sets [43].

Overall, this paper presents the performance of PPG based on previous studies. Some challenges and recommendations are presented through this paper to provide a basic reference and can be a mechanism for researchers in detecting MD signs using PPG, especially in the extraction of signal features and the development of reliable ML.

Conflict of Interest

The authors declare that they have no conflict of interest.

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