RECOGNITION OF MENTAL DISORDERS FROM PHYSIOLOGICAL SIGNALS ANALYSIS

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Abstract. The rapid advances in machine learning (ML) and information fusion have made it possible to use machines/computers with the ability of understanding, recognition, and analysis of human emotion, mood and stress, and related mental diseases. The recognition methods based on physiological modalities are the most performant. Wearable technologies enable non-invasive long-term data gathering and analysis. The number of mental health issues are correlated with emotional states and can be possibly detected by similar methods to general emotion recognition. The scientific interest in the recognition of mental disorders is growing, and most of the available studies are uni-modal based on either ECG or EEG sensor data, while some recent studies also utilize multiple modalities and sensor fusion.

Key words: Emotion recognition, posttraumatic stress disorder, major depressive disorder, physiological signals.

1. Introduction

The advancements in affective computing and recognition of human emotions, mood, and stress during the past two decades bring new opportunities for the detection, monitoring, and prevention of mental health diseases. The progress and availability of non-invasive wearable sensors and mobile technologies for computation and wireless networking enable long-term data collection and real-time sensor data analysis.

Mental health disorders, although incredibly prevalent, remain poorly understood. Anxiety disorders (AD) are the most common type of mental illness in the world, affecting 264 million worldwide. Post-traumatic stress disorder (PTSD), anxiety disorders, and mood disorders – such as major depressive disorder (MDD) and bipolar disorder (BD) – have distinct symptoms, but they overlap significantly.

According to the American Psychiatric Association, traumatic stress is characterized by the direct experience or witnessing of actual or threatened death or serious injury, or a threat to physical integrity, and responses that include intense fear, helplessness, or horror. Epidemiological studies indicate that 82% of individuals in the U.S. have experienced at least one traumatic event in their lifetime [1]. Exposure to trauma significantly increases vulnerability to a variety of psychiatric disorders, most commonly Posttraumatic Stress Disorder (PTSD) and Major Depressive Disorder (MDD). Estimates of the conditional risk for developing these disorders in the context of trauma vary widely and underscore their complex nature.

Depression is the leading cause of ill health and disability worldwide. According to the latest estimates from WHO, more than 300 million people are now living with depression, an increase of more than 18% between 2005 and 2015.

Depression is related to the normal emotions of sadness and bereavement, but it does not remit when the external cause of these emotions dissipates, and it is disproportionate to their cause. The diagnosis of the major depressive disorder requires a distinct change of mood, characterized by sadness or irritability and accompanied by at least several psychophysiological changes, such as disturbances in sleep, appetite, loss of the ability to experience pleasure, crying, suicidal thoughts, and slowing of speech and action [2].

PTSD involves a range of emotional, cognitive, and somatic symptoms that can develop after a person has experienced or witnessed a traumatic event in which serious harm to the individual occurred or was threatened. Likewise, MDD is characterized by sustained negative mood, often associated with biological, psychological, or social sources of stress. PTSD first appeared in the Diagnostic and Statistical Manual of Psychiatric Disorders (DSM-III) in 1980 arising from studies of the Vietnam war and of civilian victims of natural and man-made disasters [3].

PTSD and depression are highly intercorrelated as they are based on shared underlying psychopathological processes [4].

Given the importance of mental health, researchers are now finding ways to accurately recognize human emotions and related states that are connected to mental health disorders, to develop intervention schemes for mental health. For example, in a healthcare system with a module of emotion recognition, patients' mental and physical states can be monitored in real-time and appropriate therapy can be prescribed accordingly.

2. Drawbacks

Despite there being significant advances in the understanding of mental health diseases from one side and Affective Computing in general and particularly Emotion Recognition, the number of studies focusing on the heavily negative stress states such as sadness, depression, and related mental disorders is low. There is no general understanding of whether reliable methods of automatic recognition of such states from physiological signal analysis exist and can be further developed. Also, evidence suggests that this is not common for people with PTSD to seek treatment and that, even in academic and community mental health settings, rates of recognition may be low, with a clinical diagnosis of PTSD occurring in as few as 4% of individuals with the disorder [5-8].

3. Goal

The goal of the current article is to analyze the current state of the art in the field of recognition of human mental diseases such as depression and PTSD from physiological signal analysis, categorize recent prior works and the results achieved in terms of recognition performance, modalities used, methods applied, and conclude benefits and limitations of different methods.

4. Affective Computing

Affective computing is the set of techniques of affect recognition from data in different modalities and granularities. Affective computing research mainly comprises the topics of sentiment analysis and emotion recognition. The former performs coarse-grained affect recognition (usually a task of binary positive vs. negative or 3-class positive, negative, and neutral sentiments classification), whereas the latter involves fine-grained analysis (usually a multiclass classification of big data into a larger set of emotion labels, for example, more than 4 classes). Over the past two decades, AI researchers have attempted to endow machines with cognitive capabilities to recognize, interpret and express emotions and sentiments. All such efforts can be regarded as affective computing research.

In 1997, Rosalind Picard from MIT published her seminal book on affective computing [9], which is considered the starting point for the branch of computer science known as Affective Computing.

The general procedure of affective computing based on physiological signals is composed of the following three steps:

Step 1 – Feature extraction: Extract features from heterogeneous physiological signals from different sources including electroencephalogram (EEG), electrocardiogram (ECG), galvanic skin response (GSR), respiration, pulse rate, etc.;

Step 2 – Emotion recognition: Recognition of the emotional state; and

Step 3 – Emotional regulation: Regulation/adjustment of emotions through psychological measures.

5. Emotions and Stress Recognition

Emotion is a complex psychophysiological phenomenon. Due to its complexity, psychologists have not yet reached a consensus on a unifying definition of emotion or sentiment. There are multiple theories related to emotions or sentiments available.

Emotion is a complex state that combines feelings, thoughts, and behavior and is people's psychophysiological reactions to internal or external stimuli. It plays a vital role in people's decision-making, perception, and communication [9, 10]. Affective computing has a wide range of applications. In an HCI system, if the computer can recognize the human emotional state accurately and in real-time, the interaction between the machine and the operator can be made more intelligent and user-friendly. In military and aerospace applications, the functional state of soldiers and pilots/astronauts can be detected in real-time. Also, if the functional state can be monitored over a longer period and correlated with soldier behavior in different stressful situations, the stress tolerance and overall risk of failing or succeeding in real combat could be predicted [11].

Emotion recognition is the most important component of affective computing. It is a field of science that combines computer science, AI, psychology, and cognitive neuroscience. Human emotions mostly are identified by facial expressions, speech, behavior, or physiological signals [12, 13, 14, 15]. The first three methods can rely on widely available sensors such as cameras and microphones, however, they are subjective and the person can conceal real feelings by masking the real emotions. In contrast, emotion recognition based on physiological signals is more reliable and objective [16].

The Affective Computing research group at the MIT Media Lab has conducted a significant amount of research, demonstrating that certain affective states can be recognized by using physiological signals such as heart rate, galvanic skin response (GSR), temperature, EMG, and respiration rate. For instance, in one study the researchers elicited targeted emotions with personalized imagery and collected four channels of physiological signals (EMG, pulse rate, GSR, and respiration) to recognize up to eight classes of emotional states [17]. They extracted the time- and frequency-domain features from those physiological signals respectively. They achieved an overall classification accuracy of 88.3% for the 3-class (anger, sadness, and happiness) problem and 81% for the 8-class problem.

EEG signals are generated by the central nervous system (CNS) and respond to emotional changes faster than other peripheral neural signals. The activation of the autonomic nervous system (ANS) is largely unconscious and cannot be easily triggered by any conscious control, utilizing physiological signals from ANS (such as blood pressure, heart rate variability, skin conductivity, or respiratory rate) for emotion recognition would be robust against social masking. Heart rate is in part determined by influences on the sinoatrial node (SA) pacemaker, which is modulated by both the parasympathetic and sympathetic branches of the ANS. Additionally, experimental results revealed significant cross-cultural consistency in the ANS physiological response patterns among different emotions [18]. While ECG, PPG, GSR, Respiration, and EEG remain primary for emotion recognition, some researchers focus on novel approaches, such as electrogastrography (EGG) [19] or tongue color imaging [20].

The rapid development of mobile and wearable technologies over the past two decades made it possible to gather several physiological signals from the human body in real time. The modern smart watch can record heart rate and heart rate variability (HRV) from photoplethysmograph (PPG) sensors, electrodermal activity (EDA), skin temperature (SKT), 2-led ECG, location, and movement data via accelerometer and gyroscope. Smartphones become ubiquitous personal devices with a rich set of sensors embedded, such as an accelerometer, GPS, gyroscope, and microphone, for health monitoring, pedestrian localization, and navigation. The growing popularity of sensors, low-power integrated circuits, and wireless networks has led to the development of affordable and wearable devices that can measure and transmit data for a long period. Wearable devices are non-intrusive which is critical for long-term data gathering and minimizing observer effect. There is also a growing interest in sensor fusion from different modalities (e.g., EEG, heart rate, galvanic skin response, etc.) for emotion recognition. Over the past decade, affective computing researchers also have utilized wearable sensors and phone usage patterns to detect stress, mental well-being, and mental disorders.

6. Detection of Depression and PTSD

The everyday variations in the human emotional state reflect the mood, which can be defined as the positive or negative feelings that are in the background of our everyday experiences. Mood (anxiety or affective) disorders are psychological disorders in which the person's mood negatively influences his or her physical, perceptual, social, and cognitive processes. Some examples of such disorders include:

- Major depressive disorder – prolonged and persistent periods of extreme sadness
- Bipolar disorder – also called manic depression or bipolar affective disorder, is depression that includes alternating times of depression and mania
- Cyclothymic disorder – a disorder that causes emotional ups and downs that are less extreme than bipolar disorder
- PTSD - complex disease, a mental health condition that's triggered by a terrifying event, with four groups of symptoms: intrusive memories, avoidance, negative changes in thinking and mood, and changes in physical and emotional reactions

The relationship between mental diseases and emotions is not formally defined. Some symptoms of health diseases could be described as patterns of changing emotions in time (Fig. 1).

There is a significant overlap between major mental illnesses, such as MDD, BD, PTSD, and Complex PTSD (CPSD).

Depression is the major cause of years lived in disability worldwide; however, its diagnosis and tracking methods still rely mainly on assessing self-reported depressive symptoms, methods that originated more than fifty years ago. These methods, which usually involve filling out surveys or engaging in face-to-face interviews, provide limited accuracy and reliability and are costly to track and scale [21].

The study of PTSD dates back more than 100 years. According to the most recent edition of the Diagnostic and Statistical Manual of Psychiatric Disorders (DSM-IV-TR), the essential feature of PTSD is the development of characteristic symptoms following exposure to an extreme traumatic stressor characterized by: direct personal experience of an event that involves actual or threatened death or serious injury, or other threat to one's physical integrity; or witnessing an event that involves death, injury, or a threat to the physical integrity of another person; or learning about unexpected or violent death, serious harm, or threat of death or injury experienced by a family member or other close associate. The person reacts to this event with fear and helplessness and tries to avoid being reminded of it. The principal symptoms of PTSD are the painful re-experiencing of the event, a pattern of avoidance, and often hyperarousal.

Ghandeharioun et al. [21] developed and tested the efficacy of machine learning techniques applied to objective data captured passively and continuously from E4 wearable wristbands and from sensors in an Android phone for predicting the Hamilton Depression Rating Scale (HDRS). Input data include electrodermal activity (EDA), sleep behavior, motion, phone-based communication, location changes, and phone usage patterns. The depression severity was predicted with relatively low error. It was suggested that poor mental health was accompanied by more irregular sleep, less motion, fewer incoming messages, less variability in location patterns, and higher asymmetry of EDA between the right and the left wrists.

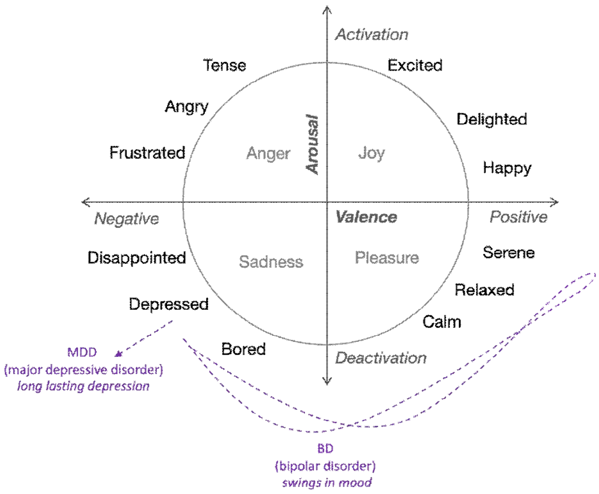

Fig. 1. Relations between emotions, MDD, and BD.

Minassian et al. [11] assessed four battalions of male active-duty Marines (N=2430) 1-2 months before a combat deployment. HRV was measured during 5 minutes of rest. Depression and PTSD were assessed by the Beck Depression Inventory and Clinician-Administered PTSD scale respectively. After accounting for covariates including traumatic brain injury (TBI), a regression indicated that lower levels of high frequency (HF) HRV were associated with a diagnosis of PTSD (beta = -.20, p=.035). Depression and PTSD severity were correlated (r= .49, p <.001), however participants with PTSD but relatively low depression scores exhibited reduced HF compared to controls (p=.012). Marines with deployment experience (n=1254) had lower HRV than those with no experience (p = .033).

Previous studies also have reported lower HRV in psychiatric disorders such as schizophrenia, depression, bipolar disorder, panic disorder, and PTSD [22-24]. Multiple studies indicate that individuals with PTSD have lower HRV, as compared to healthy controls, both at rest and during stress [25]. There is reduced parasympathetic activity (due to reduced RMSSD, HF-HRV, and LF-HRV) in individuals with PTSD, as compared to control groups. Also, the negative effect of SDNN correlates with diminished total variability in PTSD. The positive effect size in the LF/HF ratio possibly suggests changes in sympathovagal balance in PTSD, and increased HR in PTSD at baseline and during stress may indicate higher SNS activity. Results suggest that changes in the ANS in individuals with PTSD are not restricted to pure vagally-mediated HRV parameters but may rather indicate a general ANS dysregulation. Despite multiple studies suggesting a high correlation between low HRV and PTSD, it is still unconfirmed, whether lower HRV constitutes a risk factor for developing PTSD, or if lower HRV is a factor that develops during PTSD. Hence, no causal relationship can be derived.

Zhu et al. [26] propose a content-based multiple evidence fusion (CBMEF) method for the detection of mild depression, which fuses EEG and eye movement data at the decision level. The experimental results show that the proposed method outperforms other fusion methods as well as the single modality results. The highest accuracies achieved 91.12%, and sensitivity, specificity, and precision were 89.20%, 93.03%, and 92.76.

The increasing number of studies confirms the high accuracy of the detection of depression from ECG signals with ML [27]. Among the included studies, the highest classification accuracy was up to 99.5% [28], which offers the potential for screening and prevention of early clinical depression. Historically, brain activity studies were focused on magnetic resonance imaging (MRI) -based depression detection. However, EEG-based ML has achieved better performance in depression diagnosis in terms of both cost and classification accuracy [29].

PTSD affects 9% of the world population, and interestingly, seems to be less investigated in comparison to other anxiety disorders such as personality disorder (PD) [30]. Three out of four studies confirmed the correlation of HRV frequency-domain features such as high frequency (HF) and low frequency (LF) with PTSD symptoms with similar results confirmed by a medical Holter monitor (small, wearable device that records the heart's rhythm continuously over 24h) devices and Polar watch (not clinically approved). Despite some progress, many of the published results that discussed the correlation between ECG features and AD are contradictory, and many of the studies had very small sample sizes. The majority of studies are based on ECG signals only, and a few are based on ECG along with other biosignals.

The summary of the results of the studies, focused on the recognition of mental disorder states via analysis of physiological signals is presented (Table).

7. Conclusions

1. A review of the development and progress in methods and technologies in the recognition of human depressive states and PTSD from the physiological signal analysis is presented. There is a trend toward data collection from wearable physiological sensors to improve the detection of mental health diseases. While biosensors are widely utilized for capturing human emotions, the current studies on the automatic detection of mental illnesses such as depression and PTSD in most are based on a single modality such as PPG/ECG or EEG. The sensor fusion techniques are often part of the general emotion recognition pipeline, but these techniques are not as popular for mental disease detection. The timely detection of mental health issues is of great importance, as early detection and intervention can improve the outcomes of any mental disorder.

Table. Summary of selected studies in automated recognition of mental disorders

Author	Year	#	Labels	Modalities	Analysis	Rec. Rate
Jang et al. [31]	2022	71	PD	EDA, SKT, RESP, PT	SVM, Random forest, MLP	75.61%
Zang et al. [32]	2022	74	MDD	ECG	CNN	93.96%
Long et al. [33]	2021	36	MDD	ECG, PPG	LightGBM	85.32%
Movahed et al [34]	2021	64	MDD	EEG	n/a	99%
Wu et al [35]	2021	400	MDD	EEG	SVM	84.16%
Cho et al [36]	2019	55	MDD, BD	PPG	Random forest	6%-94%
Duan et al [37]	2020	32	MDD	EEG	CNN	94.13%
Tazawa et al [38]	2020	41	MDD, BD	ECG, ACC, SKT	XGBoost	76%
Shah et al [24]	2017	459	PTSD	ECG (HRV)	GEE	p <0.001
Valenza et a [39]	2016	14	BD	ECG (HRV)	SVM	69%
Minassian et al [11]	2014	2430	PTSD	PPG	ANOVA	beta = -.20, p=.035
Agorastos et al [23]	2013	15	PTSD	ECG (RR)	ANOVA	n/a

Research, which is currently ongoing, is required and it is expected that its results would enable the development of new methods and technologies.

2. Current research on relations between physiological signals is limited and the following directions for future research are suggested:

- Collection of multiple biosignals simultaneously and application of sensor fusion to merge information from multiple signals.
- Extraction of advanced features of ECG signal such as waveform morphology features.
- Application of nonlinear signal analysis and wavelet transform to extract more features.
- Collection of biosignals from wearable devices along with clinically approved devices such as ECG monitors for validation purposes.
- Building databases with a big number of subjects (>100) and from a diversity of subjects by age, ethnicity, and gender.
- Producing publicly available physiological databases that contain time-synchronized sensor data.

Although some public databases exist, these datasets are limited and most are focused on emotional states rather than mental disorders.

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9. Conflict of Interest

The authors state that there are no financial or other potential conflicts regarding this work.

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