A PATTERN RECOGNITION APPROACH BASED ON ELECTRODERMAL RESPONSE FOR PATHOLOGICAL MOOD IDENTIFICATION IN BIPOLAR DISORDERS

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ABSTRACT

This paper reports on results of a pattern recognition technique for classifying pathological mental states of bipolar disorders using information gathered from the electrodermal response. The rationale behind this work is that the autonomic nervous system dynamics, non-invasively quantified through the electrodermal response processing, is altered by the specific mood state. Starting from the hypothesis that bipolar disorders are associated with affective dysfunctions, we processed data gathered from four bipolar patients through eleven experimental trials while an ad-hoc emotional stimulation is administered. Intra- and inter-subject variability were investigated. We show that, using a deconvolution-based approach to estimate sympathetic ANS markers and simple k-Nearest Neighbor algorithms, the proposed methodology is able to discern up to three mood states such as depression, hypomania, and euthymia with an average intra-subject accuracy greater than 98% and inter-subject accuracy greater than 82%.

***Index Terms*—** Bipolar disorders, k-Nearest Neighbors, Data Mining, Electrodermal Response.

1. INTRODUCTION

Bipolar disorder (BD) is a mental illness very common in western population [1], and identified as a psychiatric condition in which patients experience drastic mood swings. Typically, BD is characterized by cyclic pathological episodes among low mood, i.e., depression, elevated mood, i.e., mania or hypomania, and a mood state in which depressive and maniacal symptoms are present at the same time, i.e., mixed state. All BD symptoms are currently treated with pharmacological therapies and, in severe BD manifestations, hospitalization is required. When BD symptoms are drastically reduced as a result of medications, patients experience relatively good affective balance (i.e., euthymic state). Current issues of BD concern the clinical diagnosis. Nowadays, in fact, the clinical practice relies on interviews and scores from psychological questionnaires as well as on the physician's own expertise and patient's subjective description. Moreover, this chronic pathology comes with comorbidity, i.e., simultaneous presence of symptoms which are shared with other psychiatric disorders, and is often undetected for years before it is diagnosed. Of note, BD diagnosis is based on the Diagnostic Statistic Manual of Mental Disorders (DSM-V-TR) [2] criteria, which defines the cut-off number of symptoms for every mental disorder, thus leading, in some cases, to biased interpretations and inconsistencies [3]. To overcome these limitations and objectifying the diagnosis, in the current scientific literature several biomarkers have been proposed taking into account biochemical markers as well as circadian rhythms (e.g. [4, 5, 6]). Moreover, it has been demonstrated that the Autonomic Nervous System (ANS) dynamics is modulated by pathological mental states associated to BD [7, 8]. In this work, we prelimininarily investigate whether features extracted from the ElectroDermal Response (EDR) can be profitably employed for the development of a viable and effective clinical decision support system for BD management. EDR, in fact, is strictly related to the Sympathetic Nervous System (SNS) [9], which is sensible to variations of emotional stimuli [10]. Therefore, being BD an emotional processing alteration, here we propose a pattern recognition approach having the following structure: EDR monitoring during affective elicitation, EDR feature extraction based on deconvolution and pattern recognition based on k-Nearest Neighbors (k-NN) algorithms. The novelties of the proposed application with respect to our previous works is described in the next section.

1.1. Novelties of the Proposed Application and Background Works

In a recent study [11], we proposed a multi-parametric platform, namely the PSYCHE system, able to provide effective support to the BD diagnosis using ANS information. More specifically, we inferred ANS dynamics by means of a personalized mood recognition analysis based on heart rate variability and respiration activity, which were non-invasively acquired through a textile-based wearable system. Moreover, we also investigated ANS by features extract from speech, to

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evaluate how much ANS variations affect also communicative channels [12]. This platform is intended to be integrated with the EDR signal acquired by means of a sensitized textile-based glove. We have already applied some statistical analysis to features extracted from EDR signals [13] from bipolar patients, achieving promising results also concerning the inter-subject classification. This work is intended to be an extension of [13], where the number of features extracted from EDR as well as the number of patients is increased and an intra-subject analysis is introduced along with an additional three-class classification. In detail, the EDR-based feature set is used as input of K-NN classifier, allowing for the recognition of three mood states such as depression, hypomania, and euthymia. The 3-class pattern recognition problem has been solved both for intra- and inter-subject classification. In the next sections, the EDR data acquisition, signal processing, and classification are described in detail along with the dedicated experimental protocol timeline. Finally, discussion of the results and conclusion are drawn.

2. MATERIALS AND METHODS

This section deals with the eligibility of the recruited patients, experimental protocol, and pattern recognition technique. Pattern recognition is comprised, in turn, of signal preprocessing, EDR decomposition, feature extraction, and classification.

2.1. Patient Recruitment, Experimental protocol and Instrumentation

We enrolled a group of 4 bipolar patients who have experienced fast mood oscillations and did not report any suicidal tendencies, delusions or hallucinations during their pathological history. Clinical evaluations were performed at the psychiatric unit of the University Hospital of Pisa. It consisted in periodical screenings through psychiatric interviews and standard evaluations based on psycho-pathological scales. At the end of the screening, a mood label among “euthymia" (EU), “depression" (DP), “mania" (MN) or “hypomania" (HMN) and “mixed-state" (MX) was associated to each patient. None of the four patients experienced a manic episode. The experimental phase foresaw two rest phases and one affective elicitation session, according to the following procedure: 5 minutes of rest with closed eyes; 5 minutes of rest with open eyes; 6 minutes-long slideshow of IAPS pictures having high arousal with random negative valence. The IAPS-pictures-slideshow is intended to provide emotional stimuli in order to evoke a response in the ANS. IAPS stands for International Affective Picture System [14], and it is a set of pictures, each of which is associated to a score of arousal and valence. Arousal refers to the emotional impact of the image, while valence refers to pleasant or unpleasant feelings evoked by the image. In the proposed experimental procedure each IAPS picture lasted for 2 seconds. As mentioned above, we hypothesized that the ANS dynamics, evaluated through EDR features, differentially reacts to such emotional stimuli according to the specific pathological mood state. The EDR signal was acquired using the BIOPAC MP150 system with a sampling frequency of $1000Hz$. The protocol was run for a period up to 75 days. A synthetic list of all the acquisitions, and associated mood label, analyzed in this study is shown in Tab. 1.

Table 1. Clinical evaluations of the patients

Patient	Acq.1	Acq.2	Acq.3	Acq.4	Acq.5
Pz01	DP	EU			
Pz02	MX	MX	DP	DP	EU
Pz03	MX	EU			
Pz04	DP	EU			

2.2. Pattern recognition: Signal Processing, Feature extraction, and Classification

Four logical blocks are included in the pattern recognition strategy: preprocessing, EDR decomposition, features extraction, and classification. In the preprocessing stage, movement artifacts were removed by visual inspection. The remaining artifact-free signal segments were used for further analysis. A low pass zero-phase forward and reverse digital filter with a cutoff frequency of 2 Hz and Butterworth approximation, was applied to limit the frequency bandwidth of the EDR signal. EDR can be split in two components: tonic and phasic. From previous studies, it is well-known how tonic represents the signal baseline (slow component), whereas phasic is the direct response to the stimulus (fast component) [9]. One of the major drawbacks in the EDR monitoring is the overlapping phenomenon, which consists of the overlapping of two consecutive phasic responses in time, and it is due, e.g., to a short inter-stimulus interval. To overcome this issue, the EDR signal is thought to be the output of a linear system, whose impulse response is $IRF(t)$, having the neural control of the SudoMotor Nerve Activity (SMNA) as input. EDR reflects changes in skin electrical properties due to sweating activity governed by sympathetic activations. Due to anatomical and physiological reasons, a compartmental pharmacokinetic model of the sweat diffusion process is defined allowing the estimation of the neural sources associated to the autonomic variations. The compartmental pharmacokinetic model adopted in this work assumes that changes in the sweat concentration is controlled only by diffusion [15, 16]. $IRF(t)$, which is also known as Bateman function, is defined as:

$$IRF(t) = (e^{-\frac{t}{\tau_1}} - e^{-\frac{t}{\tau_2}}) \cdot u(t) \quad (1)$$

where time constant τ_1 represents the fast onset and τ_2 a slow recovery. By deconvolving this function with the EDR signal we obtain the SMNA function, which can be written as

Table 2. Features extracted from phasic and tonic driver components

Feature	Description
MAX-Tonic	Maximum value of the tonic driver curve
MAX-Phasic	Maximum value of the phasic driver curve
AUC-Tonic	Area under the tonic driver curve over time
AUC-Phasic	Area under the phasic driver curve over time
Mean-Tonic	Mean value of the tonic driver
Mean-Phasic	Mean value of the phasic driver
STD-Tonic	Standard deviation of the tonic driver
STD-Phasic	Standard deviation of the phasic driver

Table 3. Confusion matrix of DP vs EU for the Patient Pz01

K-NN		DP	EU
DP	α	**100±0.00**	0±0.00
	β	**91.82 ± 7.96**	8.63±5.44
	γ	**98.19± 2.35**	0,45±1.44
EU	α	0 ±0.00	**100±0.00**
	β	8.18±7.96	**91.37±5.44**
	γ	1.81±2.35	**99.56±1.44**

$SMNA = (EDR_{Driver-tonic} + EDR_{Driver-phasic})$. Formally, it is possible to write:

$$EDR = SMNA \otimes IRF \quad (2)$$

In order to decompose the obtained SMNA signal into the $EDR_{Driver-tonic}$ and $EDR_{Driver-phasic}$ components several algorithmic steps have been processed. Further details can be found in [17] and [13].

The decomposition process was performed by means of Ledalab 3.2.2. software package for MATLAB [18]. Features were extracted from both tonic and phasic driver of EDR, i.e. $EDR_{Driver-tonic}$ and $EDR_{Driver-phasic}$. In particular, features from phasic driver component were computed within continuos non-overlapped 5-second time windows. In fact, phasic response is known to arise in a window from 1 to 5 seconds after the stimulus onset [19]. Features from tonic driver component were calculated within non-overlapped time windows of 20 seconds [20]. Details concerning the feature acronyms and description are reported in Table 2. Of note, each feature was normalized with respect to its value estimated during the first rest session. The extracted features were grouped in three sets. Specifically, we defined the feature set α as the set extracted from driver tonic exclusively; feature set β as the set extracted from driver phasic exclusively; and feature set γ as the set obtained as union of α and β sets.

The classification process aimed at performing the recognition of clinical mood states such as DP, MX, EU. In this work a k-Nearest Neighbor (k-NN) classifier was used. This choice is justified by ease of computation as well as the capability of dealing with non-parametric data of this algorithm. Remarkably, this classifier can be a viable solution to be implemented in wearable electronic devices. k-NN predicts the class finding the k closest training points, and the new example is assigned to the most common class amongst its k nearest neighbors. After the training process, the performance of the classification task is commonly evaluated using the confusion matrix. A more diagonal confusion matrix corresponds to a higher degree of classification. The training phase is carried out on 80% of the feature dataset while the testing phase on the remaining 20%. We performed 40-fold cross-validation steps to obtain unbiased classification results. In this work, classifications were performed considering both the intra- and inter-subject variability. In particular, the intra-subject study aims to classify different mood states on the same patient. Inter-subject classification, instead, considers features gathered from all the available acquisitions and grouped considering the mood label exclusively.

3. RESULTS AND DISCUSSIONS

The classification procedure was performed using all the three feature sets, namely α, β, γ, in order to assess the contribution of the tonic and phasic components of the EDR. Results, expressed in terms of confusion matrices, of the intra-subject analysis are shown in Tabs. 3-6. In three out of the four patients, the dataset γ outperformed the other feature sets suggesting that best classification accuracy can be achieved when both tonic and phasic information are included into the personalized mood recognition system. It is worthwhile that our methodology is able to solve a non-trivial 3-class pattern recognition problem achieving more than 71% of accuracy on all classes (see Tab. 6). Patients were enrolled in the study while they stayed in hospital and they were discharged when achieving the euthimic state. Pz01, Pz03 and Pz04 experienced only two mood states, while Pz02 five states. The number of patients and acquisitions is not so high, but this work is intended to be a pilot study in order to verify whether the proposed methodology is able to detect changes in the ANS dynamical patterns associated to different mood states. To further support such an experimental hypothesis we also tested the capability of the k-NN algorithm for solving the 3-class inter-subject pattern recognition problem. Results achieved using the γ feature set are very satisfactory and reported in Tab. 7. Indeed, confirming the evidences on the intra-subject recognition, when using both tonic and phasic information the system is able to achieve accuracies always greater than 80%.

Table 4. Confusion matrix of MX vs EU for the Patient Pz03

K-NN		MX	EU
MX	α	**78.18 ± 11.50**	22.27 ± 15.06
	β	**90.45 ± 5.44**	4.54 ± 6.42
	γ	**95.90 ± 5.44**	1.36 ± 2.19
EU	α	21.81 ± 11.50	**77.73 ± 15.06**
	β	9.55 ± 5.44	**95.46 ± 6.42**
	γ	4.10 ± 5.44	**98.67 ± 2.19**

Table 5. Confusion matrix of DP vs EU for the Patient Pz04

K-NN		DP	EU
DP	α	**100±0.00**	0±0.00
	β	**97.27 ± 2.35**	0.91 ± 1.91
	γ	**100 ± 0.00**	0±0.00
EU	α	0 ±0.00	**100±0.00**
	β	2.73 ± 2.35	**99.09 ± 1.91**
	γ	0 ±0.00	**100 ± 0.00**

Table 6. Confusion matrix of DP vs MX vs EU for the Patient Pz02

		DP	MX	EU
DP	α	**75.81 ± 6.77**	19.07 ± 6.65	32.27 ± 13.28
	β	**66.98 ± 7.22**	21.86 ± 5.05	27.73 ± 11.82
	γ	**78.84 ± 7.86**	10.46 ± 6.42	27.27 ± 8.01
MX	α	11.16 ± 5.11	**80.93 ± 6.65**	0 ± 0.00
	β	16.28 ± 5.69	**68.60 ± 6.69**	24.54 ± 8.88
	γ	11.16 ± 7.08	**89.07 ± 6.76**	0.91 ± 1.91
EU	α	13.02 ±6.59.00	0 ± 0.00	**67.72 ± 13.28**
	β	16.74 ± 5.98	9.53 ± 3.86	**47.73 ± 8.64**
	γ	10.00 ± 5.37	0.47 ± 0.98	**71.82 ± 0.94**

4. CONCLUSION

In this paper we proposed a pattern recognition approach to verify whether changes in the ANS dynamics through the EDR signal can be associated to mood swings in bipolar patients. The hypothesis behind is that the sympathetic control of the sweat glands (not associated to the thermal regulation) is modulated by different pathological mood states. Being the EDR signal very sensitive to a wide spectrum of stimuli, it is necessary to acquire data under very controlled conditions. We set up an experimental protocol where a resting state is supposed to be ahead of the visual emotional stimulation.

Although the proposed methodology needs to be further validated by increasing the number of patients as well as of acquisitions, the obtained preliminary results are very encouraging and promising. In the future, it will be possible to combine the EDR information with other physiological signs in order to improve the classification accuracy and reliability of the recognition. Previous works, indeed, showed that physiological patterns associated to the linear and nonlinear dynamics of the ANS control on the cardiovascular system provided significant information, even in non-controlled experimental conditions [21, 22, 23]. Moreover, as the EDR signal can be also monitored by using comfortable sensorized textile-based gloves [24, 25], it can be profitably integrated into a multiparametric wearable platform for the implementation of an effective decision support system.

Table 7. Confusion matrix of DP vs MXe vs EU using all of the samples regardless any specific patient

K-NN		DP	MX	EU
DP	α	**49.05 ± 10.78**	10.77 ± 9.21	10.00 ± 10.28
	β	**60.12 ± 4.93**	10.37 ± 2.51	17.66 ± 3.98
	γ	**80.00 ± 4.96**	8.50 ± 2.17	7.57 ± 2.39
MX	α	31.43 ± 7.17	**67.69 ± 9.28**	20.38 ± 7.03
	β	18.49 ± 4.57	**75.33 ± 4.97**	17.38 ± 4.21
	γ	9.77 ± 2.91	**83.27 ± 2.13**	8.22 ± 3.49
EU	α	19.52 ± 7.26	21.54 ± 9.100	**69.62 ± 9.32**
	β	21.39 ± 4.46	14.30 ± 3.47	**64.95 ± 5.47**
	γ	10.23 ± 3.28	8.22 ± 1.69	**84.20 ± 3.92**

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