Classification of Anxiety Based on EDA and HR

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Abstract. This work presents anxiety classification using physiological data, namely, EDA (eletrodermal activity) and HR (heart rate), collected with a sensing wrist-wearable device during a neutral baseline state condition. For this purpose, the WESAD public available dataset was used. The baseline condition was collected for around 20 min on 15 participants. Afterwards, to assess anxiety scores, the shortened 6-item STAI was filled by the participants. Using train and test sets with 70% and 30% of data, respectively, the proposed ensemble of 100 bagged classification trees obtained an overall accuracy of 95.7%. This, along with the high precision and recall obtained, reveal the good performance of the proposed classifier and support the ability of anxiety score classification using physiological data. Such a classification task can be integrated in a mobile application presenting coping strategies to deal and manage anxiety.

Keywords: Anxiety · Physiological data · Heart rate · Eletrodermal activity · Wearable measurements · Mobile applications

1 Introduction

Considering that it is of utmost importance to properly assess anxiety, recent studies stress out alterations of physiological signals related with it. Occasional anxiety, which is expected to be experienced along lifetime, is related with temporary worry or fear when facing a particular situation. Anxiety disorders go beyond temporary. In those cases, anxiety occurs frequently and at undue time,

The author acknowledge the public availability of WESAD dataset. This work was supported by the Portuguese Science Foundation (FCT) through national funds, within IEETA/UA R&D unit (UIDB/00127/2020). This work is also funded by national funds, European Regional Development Fund, FSE through COMPETE2020, through FCT, in the scope of the framework contract foreseen in the numbers 4, 5, and 6 of the article 23, of the Decree-Law 57/2016, of August 29, changed by Law 57/2017, of July 19. Moreover, this work is funded by national funds through FCT – Fundação para a Ciência e a Tecnologia, I.P., under the Scientific Employment Stimulus - Individual Call - CEECIND/03986/2018.

R. Goleva et al. (Eds.): HealthyIoT 2020, LNICST 360, pp. 112–123, 2021.
https://doi.org/10.1007/978-3-030-69963-5_8

it does not go way and get worse over time [3]. When diagnosed, the treatment can rely on medication, on behavioural therapy or on the combination of both.

In 2019, anxiety disorders were estimated to affect 4.05% of the world population, mostly women [2], with serious implications in quality of life, daily activities, workplace, families and society [20]. Anxiety disorders are affecting 301 million people, cutting across age groups, and with an increasing trend. This growing estimate are of major concern, and coping strategies to deal with anxiety disorders are of great interest. In Portugal, it affects 9.08% of the population [2], a percentage of great relevance when comparing with worldwide data.

Regarding the global rise of the consumption of antidepressants, according to the OECD (Organisation for Economic Co-operation and Development) indicators [1], in 2017, Portugal was the fifth country of the OECD with the highest consumption of antidepressants, with 104 daily doses per thousand people. Although it may be associated with a greater recognition and diagnosis of anxiety and depression disorders, it clearly reveals the increase of incidence of these disorders when compared to 2000 (when the consumption was estimated to be slightly below one third).

Considering this rise, awareness and attention need to be devoted to mental illness, and strategies to deal and manage anxiety are crucially needed. More than ever, due to COVID-19 pandemic, and considering the disrupt situation that we are facing and social distancing, anxiety can become overwhelming.

1.1 Motivation, Goals and Outline

The rational above, reinforces the urge of cognitive-behavioural therapies, accessible at a glance, helping people with anxiety disorders, presenting different ways of thinking, behaving, and reacting to anxiety-producing and fearful objects and situations [3].

Sensing wrist-wearable devices grant the easy and on the fly measurement of physiological signals, which can be integrated with a mobile application (app) for anxiety classification based on these physiological signals. Therefore, such a classification system can be integrated within a mobile app for self-management strategies to deal, in real time, with anxiety symptoms.

In a university context, this app could have significant improvements in students' well-being, helping to overcome daily and recurrent stressful situations, such as works' or projects' deadlines, exams, oral presentations, among others.

Targeting the psychophysiological perspective of anxiety, this work aims to provide motivation and support for the development of a mobile app with coping strategies to deal with anxiety, based on the ecological momentary assessment of the anxiety of the users through the analysis of EDA and HR.

Therefore, the goal of this study is to classify anxiety through physiological signals from data without any affective state elicitation. Thus, using data gathered with a Empatica wristband [7], this work presents anxiety classification, based on EDA and HR collected during a baseline neutral state condition.

The obtained results allow the identification of physiological correlates of anxiety states and can be further integrated into wearable and smart sensing contexts. Indeed, the results support the feasibility and encourage the development of a mobile app, that connected with a similar wristband, and according to anxiety score classification, can present coping strategies to deal and manage with it.

For these purposes, it was used the WESAD multimodal dataset [18], containing self-reports, motion and physiological data, recorded with a wristband (Empatica wristband) and a chest-worn device (Biosignalsplux RespiBAN Professional), of 15 participants during a lab study designed for stress and affect detection.

The remain of this work is organized as follow. Section 2 presents related works on anxiety disorders and mobile applications to deal with it. Section 3, after a brief description of the dataset used, presents the methodology used. Afterwards, Sect. 4 compares and discusses the results on relating EDA and HR with anxiety and on anxiety classification. Concluding remarks and possibilities for further research are presented in Sect. 5.

2 Related Works

In the past decade, several studies have shown that common symptoms associated with anxiety are alterations in HRV (heart rate variability), HR and sweating [6,9,10,12,13,17,18]. However, the physiological relation with anxiety is still an open problem. These findings may open new doors to cognitive behavioural therapies helping control and manage anxiety, particularly given the accessibility and affordability of new wearable technologies, such as wristbands, allowing the continuous collection of physiological data.

Moreover, these biomedical sensors are often wireless and can stream to several and small devices, like smartphones, supporting the feasibility of the analysis of physiological signals and assisting with suggestions to deal with anxiety. Indeed, more recently, due to the increasing concern on mental disorders, namely anxiety, and to the technological advances which widespread the access and usage of mobile devices, there had been proposed mobile applications to help users dealing with anxiety [4,16,19,21].

The work [8] provides a review on e-health treatments for anxiety, showing the efficacy of internet-delivered cognitive behavioural therapies to deal with anxiety disorders and identifying the limitations in engaging patients. Moreover, the authors also addressed the potential of mobile apps and virtual reality interventions for the treatment of anxiety symptoms, supporting their feasibility.

More recently, [19] provides a review supporting the use of mobile apps as helpful and accessible tools in the assessment and treatment of anxiety in youth. Although, the overall good results concerning ease of use and acceptability, and high satisfaction ratings, the authors pointed out the burdensome of user engagement over time, as well the work [8].

Regarding applications for self-management of symptoms related to mental disorders, the work [4] proposed the use of the Mindfulness Meditation app, showing the relevance of embracing HRV in the assessment and treatment of these conditions, and providing a step further in the feasibility of using HRV as a biomarker and biofeedback tool within clinical and health psychology.

Although not addressing physiological responses, the work [16] contributes with an evaluation of the effectiveness of the Feel Stress Free app, useful for the treatment of depression and anxiety symptoms. During a 6-week trial with 168 university students, this cognitive behavioural therapy-based app, which provides relaxation activities, mood tracking and thought challenging, and minigames, shown promising results to deal with depression and anxiety symptoms.

On the other hand, the work [13] proposes the assessment of mental well-being and health through a mobile application for HRV analysis, showing a positive relationship between both.

The authors of the used dataset (WESAD) provided a study on classifying different affective states (neutral, stress, amusement), using a protocol specifically designed for elicitation of the affective states [18]. Besides comparing the chest and wrist devices, in this threeclass classification problem (baseline vs. stress vs. amusement), the authors reached accuracies up to 93%.

Depart from studies relying on the elicitation of affective states, the presented work relies only on data collected during the baseline, representing a neutral state condition without any elicitation.

3 Data and Methodology

This section briefly describes the WESAD dataset, explaining the physiological signals used for the purpose of anxiety classification, the methodology to achieve them and the evaluation metrics to assess the obtained results. All the data pre-processing and processing and statistical evaluations were performed using MATLAB R2019b [15].

3.1 WESAD Dataset and Physiological Data Used

WESAD is a public available multimodal dataset[1], containing self-reports, motion and physiological data of 15 participants during a lab study designed for stress and affect detection, recorded with the Empatica wristband [7] (namely, blood volume pulse - BVP, electrodermal activity, body temperature and three-axis acceleration), and with the Biosignalsplux RespiBAN Professional chest-worn device [5] (namely, electrocardiogram, electrodermal activity, electromyogram, respiration, body temperature and three-axis acceleration). The authors also provide the average heart rate extracted from the BVP signal. According to the goals, the protocol for collecting WESAD dataset was designed with several conditions in two different combinations.

[1] https://archive.ics.uci.edu/ml/datasets/WESAD+%28Wearable+Stress+and+Affect+Detection\%29\#.

To attain the purpose of anxiety classification, this study used only the data collected during the baseline condition, which aimed to reflect a neutral affective state while participants were sitting/standing at a table with neutral reading material. For class identification, as ground truth, it was used the responses of participants, after baseline condition, to the shortened 6-item STAI (Spielberger State-Trait Anxiety Inventory), varying from a minimum score of 4 to a maximum score of 24, which offers a briefer and acceptable scale, while remains sensitive to different degrees of anxiety [14]. In the 6-item STAI, participant scored from "1" = "Not at all" to "4" = "Very much so", the following 6 conditions:

- I feel at ease
- I feel nervous
- I am jittery
- I am relaxed
- I am worried
- I feel pleasant

As the goal of this study is to classify the self-reported anxiety through physiological signals, it relies on data without any affective state elicitation, therefore data collected during a baseline condition ($mean = 19.57$ min and $std = 0.26$ min), and the results from the 6-item STAI (with summed scores ranged from 10 to 16). Figure 1 shows the EDA and HR signals for participants with minimum and maximum, respectively, upper and bottom, anxiety scores in the 6-item STAI. For these participants, from the HR signals, it can not be stressed out any pattern or trend. However, it can be observed considerable differences regarding the EDA signal, which is significantly higher for a great STAI score.

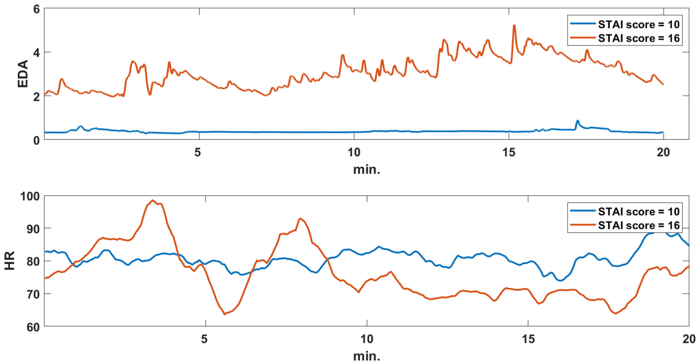

Fig. 1. EDA and HR (upper and bottom, respectively) of two participants with STAI score of 10 and 16 (minimum and maximum in this dataset).

3.2 Methodology for Anxiety Classification

Aiming at classify anxiety through physiological signals, the first step concerns the categorization of participants according to anxiety scores, which in this dataset ranges from 10 to 16, distributed according to the Fig. 2. As it can be observed, the majority class corresponds to a score of 12 in the 6-item STAI, while scores of 15 and 16, are the minority classes. Although data is not equally distributed, this work will not use any technique to deal with imbalanced datasets. Instead, it relies on other evaluation metrics, rather than only accuracy, to assess the performance of the classifier.

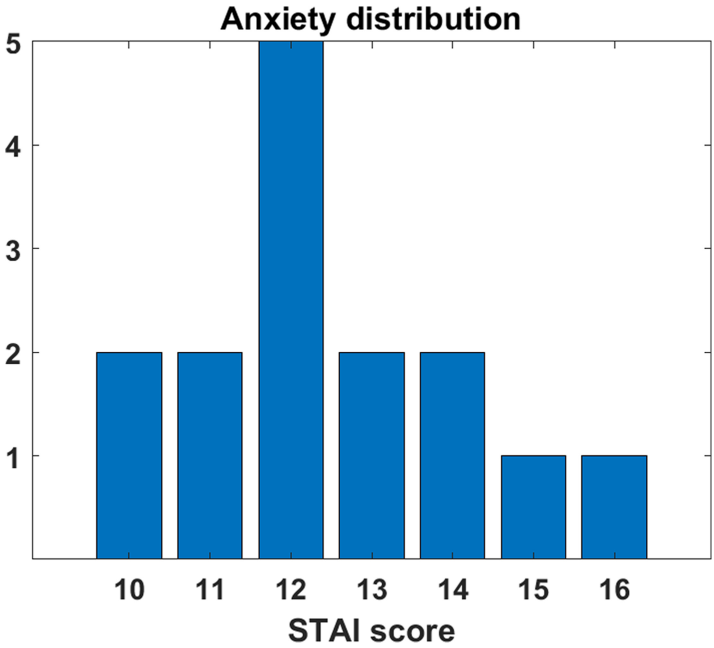

Fig. 2. Anxiety distribution, according to the score in the 6-item STAI, of WESAD dataset participants.

Regarding the EDA, collected at a sample rate of 4 Hz, and the HR, computed from the BVP, the box plots of both were analysed to explore the differences between the EDA and HR medians of different STAI scores, for all participants, during the baseline condition.

To analyse the differences between STAI scores, it was first applied the Lilliefors test to decide if data comes from a normal distributed family. Both EDA and HR failed to be normal distributed.

Therefore, to perform a global evaluation, was applied the Kruskal-Wallis (KW) Test [11], a nonparametric test, that allows to decide if the samples from the different STAI scores were originated from the same distribution, by comparing the mean ranks of EDA and HR of the different scores.

In case of differences between the score groups, those are further analysed, through multiple comparisons between the groups. In this case, is used the multcompare function from MATLAB, which besides returning the pairwise comparison results based on the KS outputs, also allows an interactive graphical multiple comparison of the groups, displaying the rank mean estimates and the comparison intervals for each group.

To decide on the best method for classifying anxiety scores through EDA and HR measured during the baseline condition, it was created an ensemble of learners for classification with data from the 15 participants, using bagging, adaptive boosting and random undersampling boosting (to deal with the imbalance of the dataset) algorithms.

Afterwards, using the best method to fit the ensemble with the EDA and HR data to STAI scores, data from baseline was used to estimate the misclassification rate and confusion matrix using 5-fold cross-validation.

Finally, this ensemble was trained with 70% of EDA and HR data, and the remain 30% of the data, held out for testing, was used on the model to make predictions.

3.3 Evaluation Metrics

The accuracy of a model is not a recommended measure to use in class imbalanced problems, as it translates performance of a model by dividing the number of corrected classifications by the total number of data examples.

Therefore, to evaluate the performance of the classifier, the confusion matrix was calculated, allowing to compute quality metrics as *Precision* and *Recall*. The *Precision* gives the ratio between the correct predictions (TP) and all the predictions of a given class, true positives plus false positives (TP+FP), and the *Recall* is defined as the ratio between the examples of a class that were correctly classified on this class, true positives plus false negatives (TP+FN). For both, the closer to 100%, the better the results are. Indeed, in the case of both get high values, then classes are properly handled by the classifier.

Combining both, the F_1 measure is the harmonic mean of *Precision* and *Recall*.

$$Precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN} \text{ and } F_1 = 2\frac{Precision * Recall}{Precision + Recall}$$

4 Results

Regarding the distribution of EDA and HR values of the 15 participants, Fig. 3 show the box plots of EDA and HR for the 15 participants under study. The left and right figures show the EDA and HR, respectively, according to anxiety scores from the 6-item STAI. The left figure points out, with 95% confidence, that the

EDA medians of the STAI scores 11, 12 and 16 are different, as the notches in the box plots do not overlap. With respect to the right figure, it shows, with 95% confidence, that the HR medians of the STAI scores 10, 11, 12, 14 and 15 are different. Therefore, using both as features to predict anxiety score would be an advantage, as one surpasses the drawbacks of the other.

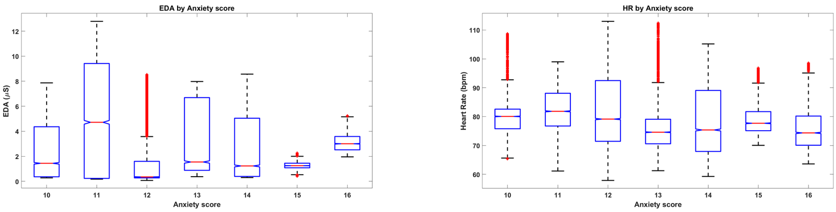

Fig. 3. Box plots of EDA and HR (left and right, respectively) for the 15 participants in WESAD dataset.

An analysis of the box plots, allows to observe the EDA and HR differences between the different anxiety scores. The EDA associated with anxiety scores 11, 13 and 14 present a higher variability, while EDA from anxiety scores 15 and 16 present smaller variability. When anxiety scored 12, EDA presented a great number of outlier values. Regarding HR, for anxiety scores of 10, 13 and 15, it can be observed a great number of outliers, while when anxiety scored 12 and 14, despite without outliers, the HR presented a higher variability.

With respect to the Kruskal-Wallis test performed using the EDA and HR data of the 15 participants, the returned p-value ($0 < 0.01$, for both cases) indicates that, at a significance level of 1%, the null hypothesis that the EDA, or HR, from the different anxiety scores (6-item STAI) come from the same distribution is rejected.

As the Kruskal-Wallis test allowed to conclude that the median values of EDA and HR from the different anxiety scores are significant different, it is performed multiple comparisons tests to reveal which from the 7 groups are significant different from the others.

Figure 4 presents the estimates of the mean rank order of EDA and HR values, and 99% confidence comparison intervals, for the anxiety scores. Regarding EDA (left), it can be concluded that groups with anxiety score of 12 and 14 have mean ranks significantly different from all the remain 6 scores, while anxiety scores 10, 11 and 15 only presented mean ranks significantly different from scores 12, 13, 14 and 16, and scores 13 and 16 have mean ranks not significantly different from each other. With respect to HR (right), with the exception of anxiety scores 10 and 15 and anxiety scores 13 and 16, that present mean ranks not significantly different from each other, the remain anxiety scores (11, 12 and 14) have mean ranks significantly different from all the remain 6 scores.

The presented analysis, concludes with the construction of a classifier, using these time series (EDA and HR) as features, to predict the different anxiety scores during the baseline condition.

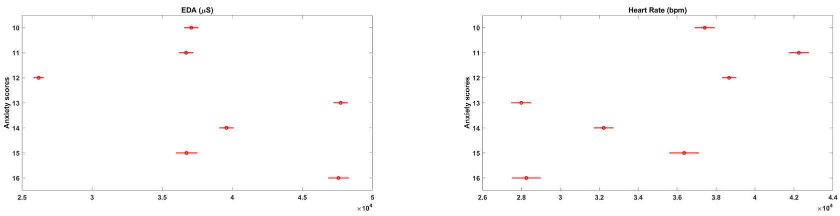

Fig. 4. Multicomparison graphics for the mean rank of EDA and HR (left and right, respectively) grouped by the 7 anxiety scores (6-item STAI).

At first, to decide on the best method for classifying anxiety scores, it was constructed a predictive classification ensemble using all available predictor variables in EDA and HR data (71684 samples, corresponding to around 20 min of baseline condition from 15 participants, collected at a sample rate of 4 Hz). After optimization, results suggested that the best method was bagging, with random predictor selections at each split (random forest).

Therefore, using all the available data, the misclassification rate and confusion matrix were estimated, using 5-fold cross-validation, obtaining an estimate cross-validated classification error of 3.77%. The obtained confusion matrix, presented in Table 1, shows, for all the classes, high values of true positives (correct predictions), displayed in the principal diagonal of the matrix, and small values (when compared to these) of true negatives, false positives and false negatives.

Table 1. Confusion matrix of anxiety classification using EDA and HR during the baseline condition.

		Predicted anxiety score						
		10	11	12	13	14	15	16
Anxiety score STAI	10	9092	55	103	141	134	36	39
	11	65	9313	123	46	38	3	0
	12	124	123	23295	82	109	158	29
	13	54	21	82	9391	67	41	0
	14	149	28	104	113	8977	20	113
	15	28	4	161	40	16	4358	9
	16	99	0	25	0	116	1	4559

Finally, due to the good results obtained so far, an ensemble of 100 bagged classification trees was trained using 70% of the data (50179 samples). The remain 30% of data were used to test the ensemble (21505 samples). Both test and train sets were constructed preserving the original class distribution.

The obtained accuracy of 95.7% is reinforced by the obtained high values for the precision, recall and F_1, which indicate a good performance of the classifier, validating its capability to classify anxiety scores using EDA and HR data. For each of anxiety scores, or classes, the precision, recall and F_1 are presented at Table 2.

Table 2. Precision, recall and F_1 measure for classifying anxiety scores using EDA and HR during the baseline condition.

Anxiety score	Precision	Recall	F_1 *score*
10	96.953	96.656	96.804
11	97.47	96.453	96.959
12	93.951	95.451	94.695
13	92.482	94.152	93.309
14	93.564	93.827	93.695
15	96.641	96.341	96.491
16	95.077	93.889	94.479

5 Conclusions and Further Research

The recent global increase of anxiety disorders and the rise of the consumption of antidepressants, demands that awareness and attention need to be devoted to mental illness. Therefore, coping strategies to deal and manage with anxiety are crucially. Moreover, sensing wrist-wearable devices, which are a minimally invasive equipment that can assess, continuously and with low-compliance, physiological signals, offers an excellent opportunity to monitor the physiological alterations under different conditions, namely stress and anxiety.

In this context, this work targets the psychophysiological perspective of anxiety, providing motivation and support for the development of a mobile app with coping strategies to deal with anxiety, based on the ecological momentary assessment of the anxiety of the users through the analysis of EDA and HR.

It proposes an ensemble of 100 bagged classification trees that, presenting an overall accuracy of 95.7% and precision, recall and F_1 means, for all classes, of 95.16%, 95.25% and 95.20%, respectively, shows to be feasible to classify anxiety scores through EDA and HR collected with Empatica, a wrist-wearable device. These results allow the identification of physiological correlates of anxiety states and can be further integrated into wearable and smart sensing contexts.

Although relying in a public available dataset with 15 participants, the encouraging obtained results sustain a future design of a protocol specially fitted to this problem.

Moreover, further research will devote efforts to develop a mobile app, that receiving physiological data collected with a wearable wrist device, classifies anxiety states and provides feedback and strategies to deal with anxiety.

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