AFFECT-STRESS MODEL

A Methodological Framework for Physiological-Based Affect as an Auxiliary Task in Stress Detection

Group 31

COGS 200

April 2023

INTRODUCTION

Prolonged states of stress, as a response to difficulty coping with the environment, is harmful to overall health and wellbeing–increasing the risk of physical and psychological illness [1,2]. Stress detection is fundamentally a classification and recognition problem, and the primary challenge lies in that stress is an ill-defined internal state with individual variability. Suggestions have been made that establish a relationship between stress states and affective states (as defined in affective computing, a referent of emotion [3]), namely, that each prompts similar physiological responses of the autonomic nervous system (ANS) [4]. We therefore propose that affect can be taken into account as a modality in a multimodal stress detection system, and hypothesise that doing so will aid in the comprehensiveness of the detection. The primary contributions of this work are as follows:

1. An affect-stress model based on the states' shared physiological signals and responses to evaluate the level of stress.
2. A stress detection system designed for implementation of this model with affect detection as an auxiliary task.

RELATED WORK

I. Multimodal Stress Detection

Commonly used modalities for stress detection include physiological signals, facial expressions (through video or image), audio, and text. The use of physiological signals has become increasingly prevalent for its capability in accuracy compared to potentially masked behavioural changes. Responses to stress have been found to include activity in the autonomic nervous system (ANS), inducing variations in physiological signals such as electrocardiogram (ECG), heart rate variability (HRV), electrodermal activity (EDA), skin temperature (SKT), and respiration [1,2,5]. The signals of HRV, EDA, and SKT are of particular interest given their direct relationship with the ANS [1,6].

The extracted features of these signals have been categorised with a binary classification of either stressed or unstressed [6,7], while others have used multi-class outputs ranging from three [8] to five [9] classes. Classification methods include support vector machine (SVM) for both binary [6,7] and multi-output classification [10], and k-nearest-neighbours (KNN) [11], naive bayes [12], and logistic regression [6] for multi-output classification. Recently, stress detection systems have utilised neural networks as a method for classification. Convolutional neural networks in particular have achieved competitive results [9].

II. Multimodal Affect Detection

The detection of affective states has been achieved from a variety of modalities including facial expressions, bodily movements or gestures, physiological signals, and semantics of natural language [13]. Early systems maintained a focus on facial expressions [14], yet have since been found to cause imprecision and discrepancies as a result of potentially blended or masked emotions that are difficult to detect. Contemporary systems have utilised physiological signals and language as primary modalities for affect detection. Physiological signals in particular have been found to contain patterns that differentiate affective states [15,16,17]. Signals of interest include blood volume pulse (BVP), heart rate variability (HRV), electrodermal activity (EDA), skin temperature (SKT), electrocardiogram (ECG), electroencephalogram (EEG), and respiration.

Two main approaches to categorise affective states are commonly taken: one uses a small set of predefined categories and basic emotions [18,19,20] while the other sorts affective states on a dimensional continuum of emotional spaces. These dimensions are "arousal" (high or low) and "valence" (positive or negative), which are divided into discrete outcomes that account for the most common affective states [4,21]. Methods of classification include SVM, KNN, naive bayes, and logistic regression. Deep convolutional neural networks (CNNs) have also become more widely used with their capability in object identification and recognition [21,23,24], and specifically multi-input deep CNNs–taking several physiological signals, performing feature extraction either in a singular branch [15,19] or in separate branches [23] to obtain feature vectors that can be classified.

III. Stress and Affect

It is clear that there exists a link between stress and affect in physiology, with variations in several signals–HRV, EDA, and SKT–taken as inputs in the detection of these states. An association can then be formed between these states as a result of their direct connection to the autonomic nervous system. The ways in which these states are animated and coped with also displays parallels: given a stimulus, the environment is appraised to be positive or negative, and endangering or assistive to the self. This appraisal then leads to changes in measurable physiological signals.

METHODOLOGY

I. Affect-Stress Model

The proposed affect-stress model is based on the shared physiological signals measured for both affect detection and stress detection, demonstrating that these signals are markers of both states and that affect can thus be taken into account within a stress detection system. HRV, EDA, and SKT are the signals used in the model. Low HRV is associated with high levels of arousal and a state of high stress [5]. High EDA, defined by high peaks in the skin's electrical conductance, is correlated with high arousal and levels of stress [24]. Changes in SKT are related to states of arousal and stress, where skin temperature increases by 0.1-0.2 degrees Celsius in high arousal and decreases by 0.1-0.2 degrees Celsius in low arousal [1]. Figure 1 illustrates the proposed affect-stress model.

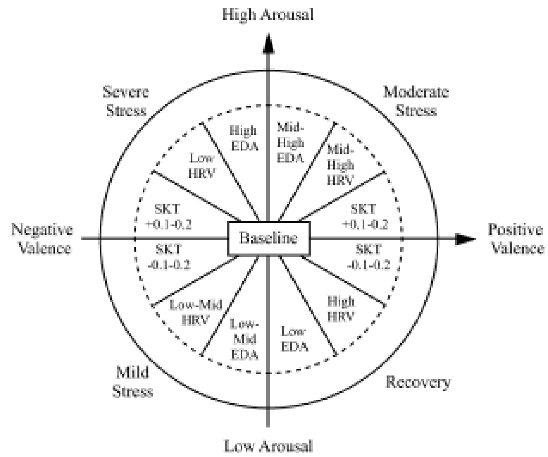

Figure 1: The proposed affect-stress model

Situated along the arousal-valence continuum of dimensional affect categorisation, arousal and valence are defined in the context of the ANS. Arousal of the autonomic nervous system is related to both stress and affective states: high activity in the ANS is correlated with higher levels of stress and greater intensity of affective experience. The appraisal of valence, the positive or negative perception of a stimulus in relation to an individual, induces activity in the ANS with the fight or flight response related to stress states and the perceived pleasantness or unpleasantness of a stimulus, in regards to affective states. By correlating these arousal and valence dimensions to the physiological signals of interest, a categorised stress state is produced.

The number of classes used for classification in the model is based on Cho et al. (2017) which evaluates four classes of stress: mild stress, moderate stress, severe stress, and recovery, as well as an individual baseline. This proposed affect-stress model represents the connection between stress and affect, and makes the case for utilising affect detection as an auxiliary task in a stress detection system.

II. Implementation of the Model

A framework is proposed to implement and test this affect-stress model in a stress detection system:

1. Data Capture: An electrocardiogram (EKG) is administered to detect HRV; EDA signals are measured via electrodes on palmar skin; SKT signals are measured with silicon temperature sensors at the wrist. A baseline diagnostic test is first taken to account for individual variability.
2. Data Preprocessing: Reducing the noise-to-signal ratio is significant to ensure accuracy and reliability of detection given its potential impact on feature stability. Noise elimination is performed on each signal, with additional baseline wander removal performed on EDA, needed as a result of free subject movement. To lessen the influence of individual variability even further, the values of each signal are normalised as a number between 1 and 100.

3. Feature Extraction: A stacked convolutional block approach is taken, with each signal organised in individual branches to allow for separate, simultaneous, and automatic extraction [22-23]. Extraction of EDA is based on convex optimization [23, 24], HRV is measured by a peak-to-peak time frame on R-wave to R-wave (RR) intervals [5], and calculations of mean, minimum, maximum, and standard deviation are extracted features of SKT [1].
4. Affect Detection and Stress Detection: The framework structure is based on a transformer model with an encoder to generate representations of the physiological signals and fuse them before classification. The multimodal features are fused by concatenating the representations into a fully connected layer. Four output units are used to predict the labels of mild stress, moderate stress, severe stress, and recovery.

III. Evaluation

To evaluate this affect-stress model and its implementation, an experiment is proposed that follows the steps outlined in the implementation. A dataset is built by exposing participants to video stimuli made to induce changes in affect and stress states, in which the physiological signals of interest are collected as described above. To account for individual variability, video stimuli could be based on individual stressors for each participant; however, this could then introduce irregularities as individual stressors would be self-reported. Following each video clip, participants complete a Perceived Stress Scale survey. Feature extraction and classification of the measured physiological signals are then performed. The final classified stress state is compared to the results of the participant's Perceived Stress Scale.

DISCUSSION AND CONCLUSION

Although implementation of this model and framework would first be evaluated in a controlled setting, applications could include measurements captured through commercial biosensors such as the Fitbit Sense 2, which contains the capacity to collect a wide range of physiological signals including those of interest. This would allow for the monitoring of stress levels on a daily basis in a more accessible approach. As the Fitbit Sense 2 automatically collects physiological data and sends to the native Fitbit app, a companion app could be created using available APIs in the Fitbit developer toolkit where stress levels could be easily monitored. Upon classification, the companion app could provide recommendations for stress management and adaptation techniques, and track stress levels over time to identify patterns and variations.

The primary contributions of this work make advances in both psychology and computer science. Contributing to psychology, the proposed affect-stress model makes the case for a relationship between stress and affect, particularly given their physiological connection. The model is presented based on variations in the patterns of these physiological signals. Contributing to computer science, a stress detection process and system is designed in which the model can be implemented and tested, using affect detection as an auxiliary task in a transformer structured neural network. This framework does not propose that the internal states of affect and stress are directly measured, but are rather derived from observations of physiological patterns and variations to detect distinct states.

Limitations are present in this proposed study. The designed stress detection system may be computationally costly given the usage of an auxiliary task and thus difficult to implement into applications such as a companion app. Future research should explore how to decrease the computational cost of this system such as through multi-task learning and sampling strategies. Additionally, the usage of the Perceived Stress Scale in the proposed experiment may cause unreliability if participants are not able to accurately self-identify stress level, whether consciously or unconsciously. Future research should investigate other methods of comparison to the classified stress level.

Monitoring stress may be valuable to many groups, particularly those who are at-risk of high stress levels for prolonged periods of time. These groups may include students, workplaces, and those with illnesses [1]. The identification of stress levels can help to reduce the risk of stress-induced illnesses or those amplified with stress by providing information that allows individuals to mediate symptoms and triggers. Prompting action allows for impact on a broader scale by increasing overall human health.

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