Determining acute physiological stress levels with wearable sensors based on movement quality and exhaustion during repetitive training exercises

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ABSTRACT

Stress is considered to have a bidirectional relationship with exercise injuries. This PhD project addresses the lack of research on methodological and measurement standards for determining acute physiological stress in the challenging context of repetitive training exercises such as squats, push-ups, and crunches. It explores how stress levels can be determined in real-time with both inertial and heart rate sensors, and how stress levels correlate with movement quality and exhaustion. To this end, a systematic method is elaborated to build a model capable of classifying stress levels with only wearable sensors in real-time.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**; • **Applied computing → Health informatics**.

KEYWORDS

activity recognition, acute physiological stress, Borg RPE scale, exhaustion, heart rate variability, inertial measurement units, movement quality, supervised machine learning

ACM Reference Format:
André Jeworutzki. 2022. Determining acute physiological stress levels with wearable sensors based on movement quality and exhaustion during repetitive training exercises. In *Designing Interactive Systems Conference (DIS '22 Companion), June 13–17, 2022, Virtual Event, Australia.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3532107.3532874

1 INTRODUCTION

Training exercises at home are often poorly or ineffectively performed due to the absence of a trainer [38]. A real-time monitoring system could serve as an early warning and feedback system [17]. Stress is considered to have a bidirectional relationship with exercise injuries: it is hypothesized that stress increases muscle tension that can lead to a motor coordination disturbance as well as a reduction in flexibility and an increase in fatigue [40]. This PhD research addresses the lack of research on methodological and measurement standards for determining *acute physiological stress* (APS) in the challenging context of repetitive training exercises (e. g., squats, push-ups, and crunches) [26, 39]. The context is challenging because there are multiple stimuli that effect a stress response and a multivariable approach is suggested [39]. For this reason, this project investigates how APS levels can be derived from *inertial measurement units* (IMUs) and *heart rate variability* (HRV) during repetitive training exercises in real-time to allow prompt user feedback. For this purpose, a model is trained based on the multi-sensor data as well as labels from movement quality assessed by sports experts and the exhaustion values perceived by subjects.

This document is organized as follows: The relevant related literature is presented in Section 2. The research question, aim, and objectives are introduced in Section 3. The novelty and contribution of this research are described in Section 4. Subsequently, Section 5 highlights the chosen philosophy and methodology for this research project. Section 6 elaborates the research method including the research setting as well as the procedure for data collection and analysis. Section 7 provides the limitations for this research. Section 8 concludes with a description of the status quo and the next steps.

DIS '22 Companion, June 13–17, 2022, Virtual Event, Australia

ACM ISBN 978-1-4503-9359-1/22/06.
https://doi.org/10.1145/3532107.3532874

2 RELATED WORK

The literature review builds on the fact that the use of data from IMUs to detect physical activity can enrich the detection of APS [41]. Therefore, the related work is approached from three perspectives: Firstly, the concept of APS is discussed; secondly, the challenge of determining APS in real-time is addressed; thirdly, APS during repetitive training exercises is covered.

2.1 Acute Physiological Stress

There is a long debate about the concept of stress in various disciplines [12]. Since each discipline has its own concepts of stress, a common definition is unlikely. Stress can be classified as acute or chronic [12, 19]. While chronic stress is pathological and psychological in nature, acute stress is the immediate response of the body to a stimulus (stressor) [11, 15, 19]. The acute response triggers alertness, energy release, physiological regulation, and immunological activation to compensate for the effects of the stressor [19]. During training exercises, the body experiences an acute stress response in which more oxygen and energy are required. The heart rate increases so that more blood is pumped through the body and thus oxygen is transported to improve cardiorespiratory function [4]. Untrained people suffer from more APS due to higher demand for oxygen and energy. Trained people become accustomed to use less oxygen; their body will eventually feel the stress over a longer period of time [4].

2.2 Determining Stress in Real-Time

As described, stress causes different physiological responses. For this reason, a single stress marker, such as cortisol or heart rate, cannot provide a global assessment of a person's stress level [39]. A multivariable approach is therefore suggested [39]. Nonetheless, determining APS algorithmically remains a challenging task: Firstly, the start, the duration, and the intensity of a stress event is often not clearly identifiable [14]; secondly, the relationship between the body's activation of biochemical stress markers and the intensity of the stress perceived is both complex and understudied [39]; thirdly, stress is highly subjective and individual —a stimulus may trigger stress in one person but not in another [14]. Nevertheless, it has been shown that sensors can be used to approximate stress in real-time, but there are no commonly accepted sensors [13, 24, 39].

Due to the multifaceted characteristics of stress, defining a ground truth for stress is another challenging task [13]. Some studies use subjective measures of perceived stress as ground truth (e. g., questionnaires or surveys) [10, 17]. Other studies rely on blood samples (e. g., cortisol or lactate) [26]. In further studies, ground truth is established by placing a subject in a neutral and in a stressful situation to label the data accordingly[10]. Similarly, some studies use the amount of workload and cognitive demand that is being applied as the stressor [39]. However, all these approaches are not suitable for monitoring APS in real-time, because they are either too time-consuming or require an artificial context [13, 39]. Recent efforts have been made to develop wearable sensors that can monitor the biomarker cortisol in real-time [30, 33], which could become an important addition to monitoring stress in real-time, but such sensors are not yet widely available.

2.3 Determining Stress during Exercises

Thus far, only a few studies have attempted to investigate monitoring stress in real-time during training exercises. Magiera et al. focused on the effect of physical and mental stress on the heart rate as well as cortisol and lactate concentrations [26]. They found that the heart rate is most sensitive to physical and mental stress. Hong et al. have outlined a two-stage classification for physiological analysis and recognizing stress during physical activities [20]. Wong et al. used IMUs in combination with physiological data [41]. They concluded that physiological signals alone cannot distinguish well between activities and stress. Alamudun et al. proposed two multivariate signal processing techniques to reduce the effect of interference caused by physical activities [1]. Maier et al. described a smartphone app that considers physical activity based on contextual data and uses mood maps to continuously determine individual stress levels [27]. Many studies focus on binary stress detection (stress or no stress) [14, 28]. However, stress is a natural response of the body during training exercises, it is therefore necessary to differentiate between multiple levels of stress, which has been investigated in a few studies [18, 28, 36].

3 RESEARCH QUESTION

The hypothesis for this research project is that a combination of multiple variables derived from IMUs and HRV can be used to determine APS levels during repetitive training exercises. The APS levels are derived from subjective data consisting of perceived exhaustion values and assessed movement quality. To simplify the assessment of movement quality, only repetitive training exercises are examined, since a beginning and an end are easier to identify. IMUs were chosen because they are directly related to physical activity and thus to movement quality [38]. HRV was chosen because it correlates with the autonomic nervous system and the intensity of physical activity [4, 19]. This project attempts to answer the following research questions:
RQ1: How significant is the correlation between movement quality, exhaustion, and sensor data?
RQ2: What variables based on wearable sensors are most representative of APS during repetitive training exercises?

The aim is to determine APS levels with wearable sensors in real-time. To achieve this, the following objectives are pursued:
OBJ1: To develop a systematic method that results in a model for determining APS levels during repetitive training exercises.
OBJ2: To create a model capable of monitoring APS levels with only wearable sensors in real-time.
OBJ3: To elaborate a set of variables needed to determine APS levels with wearable sensors.

4 NOVELTY AND CONTRIBUTION

An objective, reliable correlation between physiological variables and perceived stress has not yet been found [24]. Moreover, there is no commonly accepted method for determining stress levels [12, 28, 39]. Blood samples, such as cortisol, are considered reliable and are used as a baseline in stress-related studies [2, 39], however, such obtrusive stress variables are not applicable for monitoring stress in real-time [28, 39]. Unobtrusive stress markers based on wearable sensors can be used to measure stress in real-time but they are less reliable [24, 39]. The author is not aware of any studies that have linked movement quality, exhaustion, and real-time stress monitoring. This project will therefore contribute a systematic method and a set of variables to determine APS levels during repetitive training exercises in real-time with wearable sensors.

5 RESEARCH DESIGN

This project follows a positivism research philosophy and a deductive approach [34]. The potential correlation between sensor data, exhaustion, and movement quality is investigated with an experiment research strategy [34] based on a multi-method quantitative research design to collect and analyze data [34]. The methods are: multi-sensor data collection, survey scales, data labeling, data mining, and hypothesis testing. Data sets are collected in a study with several sessions. One participant per session. The main variables are features, a numeric representation of raw data [42], derived from IMUs and HRV data as well as ratings of perceived exertion and assessed movement quality. Ethical considerations are necessary in relation to volunteers whose movement and physiological data is collected and analyzed; cardiac data in particular is sensitive information as it can be used to identify diseases.

6 METHOD

This section is organized as follows: Firstly, the research setting is presented; secondly, the sample selection is described; thirdly a systematic method for data collection is elaborated; and fourthly, the process of data analysis is explained.

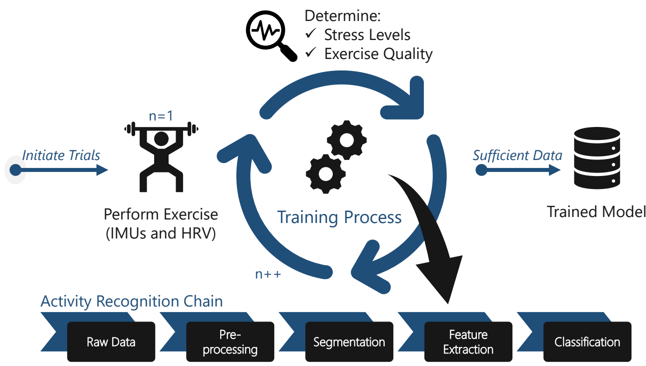

Figure 1: Overview of the training process.

6.1 RESEARCH SETTING

The study takes place in the *Creative Space for Technical Innovations* (CSTI) laboratory, where the author is employed as research assistant and where an experimental setup has been established as part of an interdisciplinary European-funded project called MoGaSens. The aim of MoGaSens was to develop a real-time feedback application based on a wearable body sensor system for fitness-oriented training at home. This PhD project originated from the MoGaSens project, but with a sole focus on APS. Moreover, the MoGaSens project has resulted in a long-term collaboration with sports experts available for this PhD research. The experimental setup consists of wearable sensors (MetaMotionS 9-DOF IMUs by MbientLab Inc and H10 chest strap by Polar Electro Oy), infrared cameras by ART GmbH & Co. KG to track body movement with body-worn markers for verification purposes, and c920 webcams by Logitech International S.A. to record participants during the training exercises.

6.2 Sample Selection

Related studies recruited a varying number of (healthy) participants to reach sufficient results: for example, while Seiffert et al. recruited two participants [35], Morris et al. gathered data from 114 people [29]. Mishra et al. observed that most studies recruited a relatively small number of participants belonging to a narrow demographic group [28] —often no more than 20 participants (e. g., [5, 16, 21, 25, 31]). A similar cohort is targeted for this research. In addition, a balanced set of training data is targeted to avoid class imbalances that would affect classification performance [37]. For this reason, healthy students of similar age and fitness level are recruited to avoid an unequal distribution. For example, the ratio of athletic to non-athletic participants would profoundly affect classification in such small study groups. However, Morris et al. [29] point out that variations inevitably affect recognition accuracy and encourage large-scale training. The author is unaware of any general rule of thumb regarding a minimal required number of participants to reach satisfactory classification performance at scale.

The repetitive training exercises are selected in advance to approximate the fitness level of the invited group of participants: the aim is to avoid under- or overexertion of the participants. In the case of underexertion, the data collected does not allow differentiation of the perceived APS levels. In the case of overexertion, a session may have to be aborted prematurely.

6.3 Data Collection

Data is collected while conducting training exercises with volunteer participants at the CSTI. Figure 1 outlines the overall training process. Technically, the data collection is based on the five steps of the Activity Recognition Chain which is described in Section 6.4.

In each session, only one participant and the author are present (hereinafter also referred to as instructor). Each session begins with the instructor informing the participant about the general process and goal of the study. A description of the collected data and its purpose is provided; data sets are collected from four IMUs, a heart rate sensor, labels for movement quality, and the *ratings for perceived exertion* (Borg RPE Scale) [7]. The participant confirms consensus by signing a consent form. The participant is then asked for a self-assessment of the general and current fitness level as well as the currently perceived level of exhaustion.

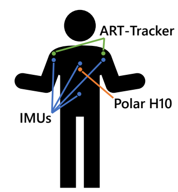

Figure 2: Sensor placement (front view).

The training process for data collection begins by wiring the participant with the wearable sensors (see Figure 2). The participant receives a short demonstration of each individual training exercise. The participant then performs a set of training exercises according to verbal instructions. A general laboratory protocol was adapted from Mishra et al. [28]: Figure 3 illustrates the timeline of the laboratory protocol with a set of seven repetitive training exercises selected by sports experts and adopted from the MoGaSens project. The sensor data is collected throughout all exercises including rest phases. After completing each exercise, the instructor asks the participant to state a rating of perceived exertion on the Borg RPE Scale. The set is repeated a total of three times with the same participant, with a rest period of three minutes between sets. The whole session takes about 75 minutes per participant. After all three sets have been completed, the process is repeated with a new participant until sufficient data has been collected (see Section 6.2). The movement quality of each repetition is assessed (labeled) by sports experts based on the recorded videos, as the experts can watch each repetition at a slower speed.

6.4 Data Analysis

A commonly used general-purpose framework to design and evaluate activity recognition systems is the *Activity Recognition Chain*

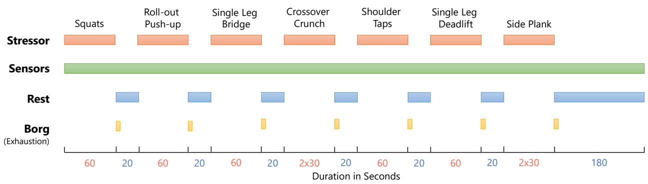

Figure 3: Laboratory protocol for a set of seven exercises.

(ARC) [35]. The ARC was introduced by Bulling et al. [9] and consists of the following five steps: raw data, pre-processing, segmentation, feature extraction, and classification. In principle, the ARC provides a schematic illustration for converting multimodal sensor data into classified information, but the actual implementation is left to the developer. The following describes how the five steps are implemented to create a model that determines APS levels with wearable sensor data and Figure 4 shows how the data is mapped for an exemplary sequence of five squat exercises.

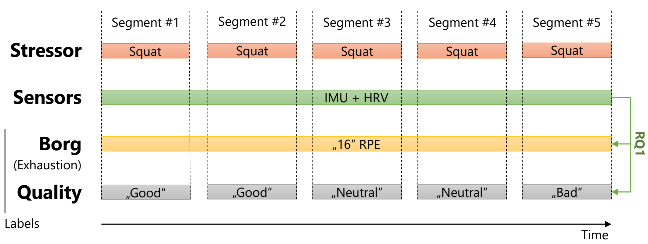

Figure 4: Sensor data mapped to movement quality and exhaustion based on individual segments (repetitions).

The first step is collecting the raw data from multiple sensors as described in the previous Section 6.3.

In the second step, the collected data is pre-processed. Based on related studies (e. g., [16]), the Euclidean norm is used to combine the x-, y-, and z-axes for each IMU sensor into one signal. In doing so, it is no longer necessary to determine which of the three axes is most meaningful for distinguishing a particular exercise. Additionally, an exact orientation of the body-worn IMUs is no longer required. This is because the gravity measured by the IMUs is distributed over the three axes and the Euclidean norm combines the magnitudes in one signal. Subsequently, noise and outliers are removed by filtering the data with the Butterworth filter [6]. In initial tests, the Butterworth filter has proven to be efficient for real-time applications, producing smooth signals that are beneficial for the following segmentation approach.

In the third step, the pre-processed data is segmented into individual repetitions based on the data of the IMUs. The literature indicates different means to accomplish repetition detection such as minima and maxima searches [25], also known as Zero-Velocity Crossing [8]. Due to its simplicity, Zero-Velocity Crossing is prone to oversegmentation (too many detected segments), but it is efficient for real-time applications [8] and has shown to be sufficient for repetitive training exercises in initial tests. Additionally, all data pass through a sliding window to reduce the amount of data processed simultaneously; this also allows quick user feedback for potential applications such as a digital personal trainer app.

In the fourth step, features are calculated for each segment (i. e. repetition). Different types of features exist for this task, such as dynamic [6], statistical [16], or frequency-based features [3]. The selection of appropriate features is critical in influencing the accuracy of a trained model to successfully detect repetitions [22] and is a part of this research (RQ2). A feature vector is calculated and consists of a summary of calculated values (e. g., mean, median, and variance) that are passed to the final classification step. The subjective data (labels for movement quality and ratings of perceived exertion) are added to each corresponding feature set (repetition).

In the fifth step, a model is either created or used for real-time classification. The model incorporates trained classifier(s) that can determine movement quality, exhaustion, and APC levels for each repetition. Supervised machine learning is planned, but other statistical techniques are being investigated as well. Examples for suitable machine learning classifiers are *support vector machine* (SVM) [31], decision trees [22], random forests [6], and Naive Bayes classifiers [5], whereas most of the mentioned studies leveraged and compared a set of different classifiers. While there is no clear consensus as to which classifier performs best, several studies have found SVM and random forest perform better than other models which also tend to limit over-fitting, reduce bias, and variance [28, 32].

7 LIMITATIONS

The scope of this research is limited to APS caused by repetitive training exercises in an laboratory setting. Other sources of stress exists such as fatigue, discomfort, or illness, but these effects cannot be completely avoided. A further limitation is the assessment of movement quality, which is a controversial topic in sports science.

Figure 5: Preliminary study with crunches.

8 NEXT STEPS

A method for data collection and analysis has been developed and tested in initial trials based on a custom implementation of the ARC (see Figure 5). A preliminary set of statistical features from [16] was used to classify activities [23]. Since the data collected so far is small, new data will be collected in an upcoming study. The next step is to investigate different feature sets and classifiers.

ACKNOWLEDGMENTS

Supervisors of the University of Applied Sciences Hamburg: Prof. Dr. Kai v. Luck, Dr. Susanne Draheim, Dr. Jan Schwarzer.
Supervisors of the University of the West of Scotland: Prof. Dr. Qi Wang, Prof. Jose-Mario Alcarez-Calero.

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