Mmsd: A Multi-modal Dataset for Real-time, Continuous Stress Detection from Physiological Signals

Mouna Benchekroun[1,2][a], Dan Istrate[1][b], Vincent Zalc[1][c] and Dominique Lenne[2][d]

[1]*Biomechanics and Bioengineering, UMR CNRS 7338, Université de Technologie de Compiègne, Compiègne, France*

[2]*Heudiasyc (Heuristics and Diagnosis of Complex Systems), Université de Technologie de Compiègne, Compiègne, France*

Keywords: Multimodal Dataset, Emotion Recognition, Stress Detection, Physiological Data, Affective Computing.

Abstract: Although chronic stress is proven to be very harmful to physical and mental well being, its diagnosis is punctual and nontrivial, which calls for reliable, continuous and automated stress monitoring systems that do not yet exist. Wireless biosensors offer opportunities to remotely detect and monitor mental stress levels, enabling improved diagnosis and early treatment. There are different algorithms and methods for wearable stress detection, however, only a few standard and publicly available datasets exist today.

In this paper, we introduce a multi-modal high-quality stress detection dataset with details of the experimental protocol. The dataset includes physiological, behavioural and motion data from 74 subjects during a lab study. Different modalities such as electrocardiograms (ECG), photoplethysmograms (PPG), electrodermal activity (EDA), electromyograms (EMG) as well as three axis gyroscope and accelerometer data were recorded.

In addition, protocol validation was achieved using both subject's self-reports and cortisol levels which is considered as gold standard for stress detection.

1 INTRODUCTION

Stress can be defined as a complex reaction pattern with psychological, cognitive and physiological components. The stress response occurs whenever there is a homeostatic imbalance caused by internal or external factors (Ursin and Eriksen, 2004).

While generally adaptive and safe in the short term, the presence of stress over the long term can be harmful to a person's mental and physical health (Yaribeygi et al., 2017). For example, chronic stimulation of the cardiovascular system due to stress leads to sustained increases in blood pressure and vascular hypertrophy. Stress is also linked to immunosuppression by directly affecting a variety of hormones involved in immune system function such as cytokines profiles (Schneiderman et al., 2005),(Yaribeygi et al., 2017).

The gold standard stress measurement modality today is salivary cortisol levels. This measure remains however punctual and delayed. It does not allow for real-time stress monitoring.

Since the stress response has psychological determinants as well, stress is among the psychological concepts that can be measured through questionnaires. Several psychologists looked into the question and developed questionnaires covering a wide range of psychological symptoms caused by exposure to chronic stress. State and Trait Anxiety Inventory ($STAI$), for example, is the gold standard for measuring preoperative anxiety (Dalal et al., 2015).

The same way as cortisol, questionnaires offer a punctual measure. Furthermore, they are based on subjective feedback which is not always reliable.

Given the gap in this area and the value of continuous real-time stress monitoring, scientists have attempted to quantify stress by measuring changes in physiological parameters such as heart, skin and muscle activity.

Thanks to biosensors that have developed a lot in recent years, it is possible to collect various physiological data during users daily life and automatically extract information about their physiology.

Approved medical devices exist today such as the "*AppleWatch*" and the "*WithingDevices*" watch which assesses stress from the heart rate and Heart Rate Variability (HRV). The *Empatica* bracelet and the *PIP* device are based on skin conductance,

[a] https://orcid.org/0000-0001-5833-5776
[b] https://orcid.org/0000-0001-5906-4947
[c] https://orcid.org/0000-0001-5325-6649
[d] https://orcid.org/0000-0002-6225-8854

Benchekroun, M., Istrate, D., Zalc, V. and Lenne, D.
Mmsd: A Multi-modal Dataset for Real-time, Continuous Stress Detection from Physiological Signals.
DOI: 10.5220/0010985400003123
In *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2022) - Volume 5: HEALTHINF*, pages 240-248
ISBN: 978-989-758-552-4; ISSN: 2184-4305

whereas the *SpireStones* device monitors subject's breathing frequency to identify stress.
The main drawback common to these commercial devices is the use of a single signal to detect stress, which reduces their reliability since different psychological, or even physical states can have similar impacts on the same signal.

Since stress is now recognized as a universal premorbid factor, associated with several risk factors for various chronic diseases, there is a need to improve stress monitoring not only in clinical practice, but also for prevention and early intervention, which is essential to avoid complications due to cardiovascular diseases (Schneiderman et al., 2005). Affective computing as an emerging field could also benefit from a continuous real-time stress detection device to improve human-computer interactions.

2 RELATED WORK

In recent years, many studies have been conducted on stress detection from physiological parameters. Besides signals such as electrocardiograms (ECG), photoplethysmograms (PPG), electrodermal activity (EDA) $\ldots$, some scientist take interest in outward characteristics like body posture and facial expressions. In our study, the focus is put on physiological signals as they are less sensitive to environmental variations or noise.

Most of the studies published today are conducted in laboratory environments using various stressors such as public speaking, mental arithmetic and stroop color word test (Adochiei et al., 2019). Others use physical stressors as a cold pressor for example and hand grip (Dickerson and Kemeny, 2004).

Although there is intensive research in the field of stress monitoring from wearable devices, there is only very little publicly available data.

One of the first datasets on continuous stress monitoring was published by Healey et al (Healey and Picard, 2005). The dataset includes ECG, trapezius EMG, EDA and respiration from 24 subjects during 50min real-world driving. Protocol validation was achieved by questionnaires and video coding for part of the subjects. This is one of the rare studies that has been carried out in an ambulatory environment

Koestra et al also published a dataset for emotion analysis, including stress, using physiological signals (Koelstra et al., 2011). Electroencephalograms (EEG) as well as ECG, PPG, EDA, trapezius EMG and respiration were recorded from 32 subjects while they watched 40 videos each inducing a different emotional reaction. Labeling was achieved by subject's self assessment after each trial (Koelstra et al., 2011).

Another publicly available dataset is the $SWELL-KW$ published by Koldijk.S et al (Koldijk et al., 2014). The dataset was collected in an experiment on 25 subjects in their work spaces while they performed typical knowledge work under stressful conditions such as time pressure and email interruptions. Various data including computer logging, facial expression, body postures, ECG and skin conductance were recorded in neutral and stressful conditions. In this study, ground truth was obtained through subjective rating thanks to various validated questionnaires such as the Nasa Task Load Index used to determine task load (Hart and Staveland, 1988) and Self-Assessment-Manikin Scale (SAM) for emotion response (Bradley and Lang, 1994) and other questionnaires.

More recently, *Schmidt et al.* published a multimodal dataset of physiological and motion data of 15 subjects during a lab study targeting three different affective states: neutral, stress and amusement (Schmidt et al., 2018). The recorded data include ECG, PPG, EDA, trapezius EMG, respiration and three axis acceleration. Subjective feedback was used once again as ground truth through different established questionnaires such as the Positive and Negative Affect Schedule ($PANAS$), a 6 item STAI, a (SAM) and a Short Stress State Questionnaire ($SSSQ$).

One common disadvantage to all the studies cited above is the small sample size generally below 30 participants. Moreover, it is true that self-assessment is important to have personal feedback from the subject, but one has to keep in mind the bias of such subjective assessment, especially when using hand-crafted questionnaires that haven't been experimentally tested and validated. Subjects may indeed have trouble identifying their emotions.

For a more reliable validation, established psychological questionnaires should be backed up by the gold standard stress measurement which is cortisol level.

A longitudinal study was carried out, few years ago in our lab, that aimed to recognize stress during users daily routine. Three sensors including an actigraph, a punctual blood pressure manager and a $PolarH7$ belt for heart activity were used to record 53 subjects during 14 days of their daily lives (Tlija et al., 2019).

The end goal was to study the correlation between emotional states including stress levels and prognosis of cardiovascular disease, but it was too ambitious to start with a long-term, ambulatory study for emotion recognition for two reasons:

1. Study duration was too long for subjects to stay committed all along and follow all the guidelines.
2. Signal segmentation could not be achieved reliably because labeling was based only on subjective journaling which was often not done carefully by the subjects.

Given the difficulty of such longitudinal ambulatory user studies, we chose a more constrained study carried out in a laboratory environment as a starting point. The exact protocol is detailed in the next section.

Paper Contribution

In this paper, we present a multi-modal dataset for stress detection from physiological signals. Our dataset bridges the gap between uni-modal devices now available and potentially more reliable multi-modal stress measurements based on physiological signals.

To the best of our knowledge, it is one of the largest datasets available on stress monitoring.

The experimental protocol is described with great detail so that the potential user can have a global view and a deep understanding of the data.

Physiological differences and constraints such as cortisol fluctuation and subjects profile were taken into consideration in the study design. The experimental protocol is validated with gold-standard stress measures which makes it suitable for stress detection through artificial intelligence algorithms.

3 VARIATIONS IN STRESS RESPONSES

When studying any physiological reaction of the human body, one has to be aware of the sources of variation affecting the response.

Stress is a highly personalized phenomenon that varies between people depending on individual vulnerability and resilience, and between different types of tasks (Fink, 2016). Parameters affecting the stress response can be categorized as follows:

- Stressor's type: Subject's stress response depends on the intensity/severity of the stressor, its controllability as well as personal features that determine the cognitive reactions to each stressor type (Schneiderman et al., 2005).
- Subject dependant variations: Each individual's response to stress is determined by a multitude of genetic, personal and environmental factors. Coping skills, personality, psychiatric history and sociodemographic variables also have an important impact on the stress perception and recovery (Kendler et al., 2003).
- Activity dependant variations: Stress response characteristics also vary with physical activity (walking VS running, standing VS sitting ...) (Alamudun et al., 2012). *Shumm et al.* found that EDA is sensitive to subject's movement. They concluded that the faster a person is walking the more uniformly distributed the skin conductance (Schumm et al., 2008).
  Heart rate is also subject to posture-related changes. A significant increase in heart rate as a subject transitions from supine to sitting; from sitting to standing, and from standing to walking has been reported in a study carried out by (Van Steenis and Tulen, 1997).

These variations should be taken into consideration when designing a user study for stress detection. Efforts should be made to tackle these sources as much as possible by controlling the stressors, the environment and subject-related variations by establishing a subject profile.

It is true that the end goal is ambulatory stress detection in user's daily life, but this requires to test and validate continuous stress detection methods in constrained environments, where these sources of variation are kept to a minimum, as a first step.

Another very important aspect in such studies is the use of gold-standards for protocol validation.

4 DATA COLLECTION PROCESS

Once our experimental protocol was approved by The INSEAD Institutional Review Board (IRB : 202077), INSEAD Behavioural Lab team took charge of subject's recruitment and management. Participants (aged 18 and older) were invited by email to take an online survey (the pre-selection questionnaire introduced below) in order to verify their eligibility to the study.

4.1 Eligibility Criteria Selection

Subjects had to be selected in accordance with ethical criteria as well as the constraints related to the study itself.

A pre-selection questionnaire was used as a first step in volunteers selection process with four objectives:

1. Exclude Non Eligible Volunteers:

   Subjects were selected in order to have a statistically representative sample of the french population in terms of age and gender. Exclusion criteria included volunteers suffering from: cardiovascular diseases, chronic diseases (diabetes, hypertension and mental disorders (depression, dementia ...) since these conditions may have an impact on the collected physiological data.

2. Build a Subject Profile:

   The pre-selection questionnaire was also used to collect general information about lifestyle elements that would potentially affect the stress response such as: the participant's level of physical activity, eating habits, sleeping habits, meditation, ...
   These elements could be used in data interpretation.

3. Enunciate Guidelines:

   Guidelines were given in the pre-selection questionnaire to check volunteer's acceptability to wear the biosensors and their willingness to respect some instructions. For example, selected subjects were asked to abstain from alcohol, caffeine/theine and tobacco, 12 hours, 4 hours and 2 hours respectively before the experiment.

4. Measure Perceived Stress:
   The questionnaire also includes a PSS4 (Perceived Stress Scale) consisting of 4 questions. This scale assesses the state of perceived stress and measures the degree to which situations in one's life are appraised as stressful (Warttig et al., 2013).

4.2 Participants

227 participants volunteered to take part of our study. 57 were rejected due to exclusion criteria and 74 healthy subjects were selected from the remaining volunteers. Our objective was to form a representative sample of the French population in terms of age and gender. Figure 1 summarizes the selection process. The final sample includes 38 women aged 19 to 63 years old (mean age: 33 y.o $\pm$ 12.5) and 36 men aged 21 to 79 years old (mean age: 35 y.o $\pm$ 13).

4.3 Sensors

For data collection, we used Shimmer Sensing biosensors for all physiological data. Four signals were selected to study their correlation with stress: electrocardiogram (ECG), photoplethysmogram (PPG), electrodermal activity (EDA) and electromyogram (EMG). Sensors configuration is depicted in figure 2

ECG is recorded using four self-adhesive electrodes for three leads included in Einthoven triangle. Two electrodes were placed across the heart, below the collar-bones, a third one below the chest, and the grounding electrode in the middle chest.

Pulse is recorded thanks to a transmission Photoplethysmograph sensor (PPG) from the right earlobe. Transmission PPG sensors detect light passed through the tissue and are therefore commonly used on peripheral sites such as fingers and earlobes. We chose the latter location since it is less sensitive to motion artefact and tissue alterations caused by both voluntary and involuntary movements as there is no muscle activity.

Electrodermal activity is recorded with sticker electrodes on the participant's non dominant hand. One electrode is placed on the palmar surface of the index medial phalange and the other on the palmar surface of the middle fingers' distal phalange.

For trapezius muscle activity, positive and negative electrodes are placed in parallel with the muscle fibres, near the centre of the right and left muscle, 2cm apart from each other. The reference electrode is placed at the elbow as an electrically neutral point of the body far from the muscle being measured.

ECG, pulse and EDA are recorded at 512Hz whereas EMG is digitized at 1024Hz.

Recorded data was stored locally in sensors SD card and transferred at the same time via Bluetooth to a computer for further processing after the experiment. Shimmer Sensing software (ConsensysPro) was used to manage data and devices.

All the devices used in the study are equipped with gyroscope sensors that can measure the orientation and angular velocity of the device. Three axis gyroscope data is available for each of the sensors introduced above.

Computer logging including response time and task duration were also automatically saved to an SQL database.

4.4 Experimental Protocol

The goal of this study is to elicit three different affective states (relaxation, stress and neutral) and identify correlations between physiological signals and these states.
To minimize the effect of the different sources of variation on the stress response, the study is carried out under laboratory conditions, where the environment is

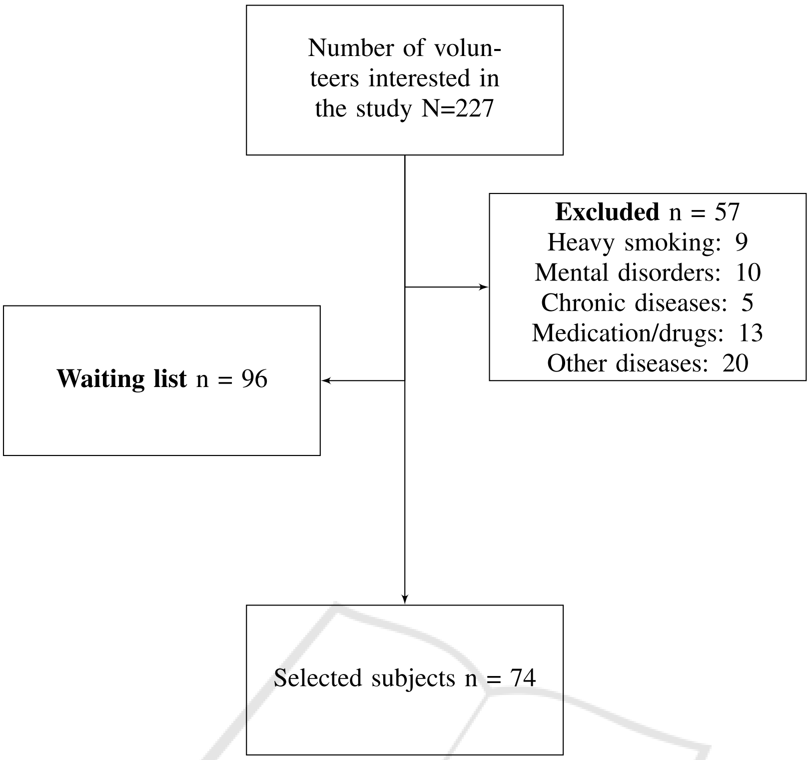


Figure 1: Subject selection process.

controlled and movement is reduced. The experimental protocol is detailed below and depicted in figure 3:

1. **Relaxation/Meditation:** Subject is invited to relax thanks to a 15min guided meditation session instructed via an audio track. Subjects followed the instructions with closed eyes, while sitting in a comfortable position in a dark environment.

2. **Stress:** Subject performs various stressful tasks such as the Stroop color word test, mental arithmetic and other serious games previously proven to induce mental stress (Dickerson and Kemeny, 2004). A score as well as a red timer are used to increase pressure. Subjects were not aware that the main goal of this step is to induce stress. Instead, they were told the tasks are used to compute a QI score.
This phase lasted for around 20min.

3. **Recovery:** At the end of the protocol, data was recorded for an additional 10min while subject is asked to stay seated with a calm music background.
The purpose of this step is to evaluate how subjects recover from a stressful stimuli.

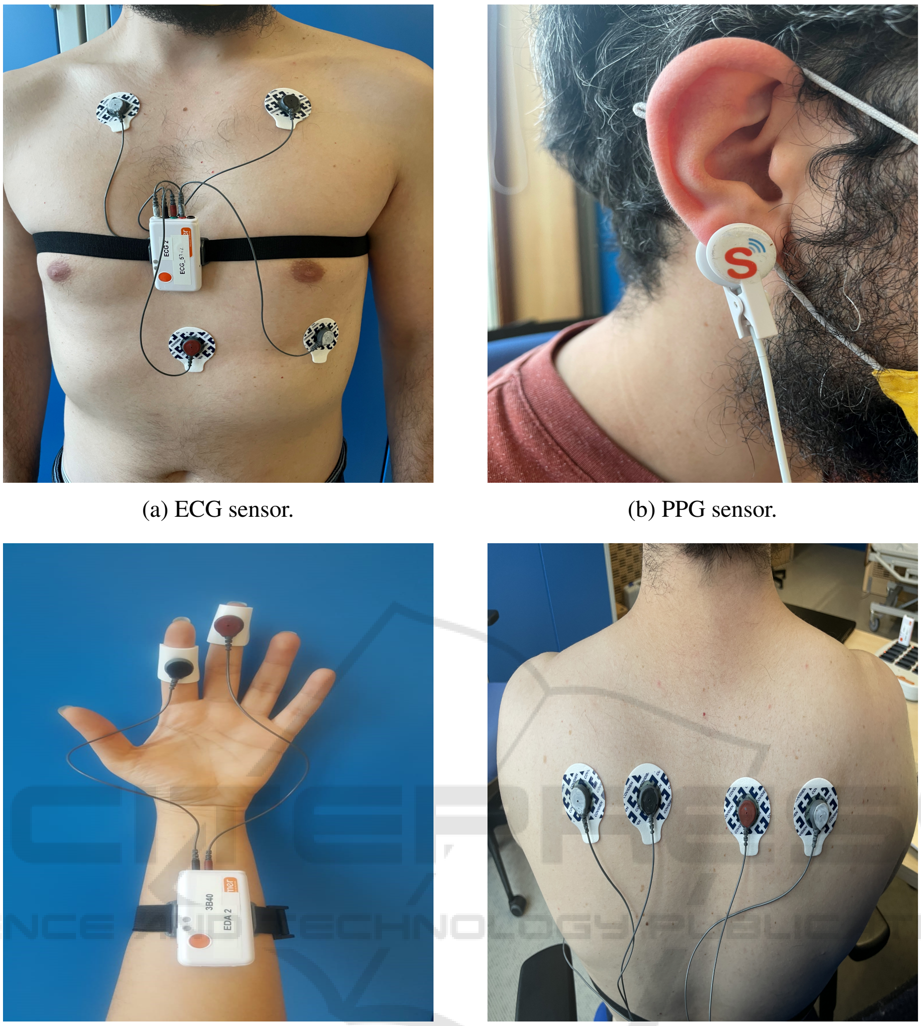
The study lasts for about 80 minutes. All the trials took place in the afternoon in order to avoid the wake-up cortisol peak and because cortisol levels are steadier in the afternoon (Dickerson and Kemeny, 2004).

4.5 Labeling and Protocol Validation

Since the main purpose of our study is to use machine learning algorithms to classify each state, we needed to validate our protocol beforehand in order to make sure subject's affective state matches the experimental protocol. Two different measures were used as labels:

1. Cortisol Samples:

   Saliva samples were collected after the first and second phases (baseline and stress respectively) as a gold standard measure of stress. We expect cortisol levels to be higher in the second sample with comparison to the first one. Since cortisol levels vary throughout the day with the highest peak reached few hours after waking up, as explained earlier, all trials took place in the afternoon (after 2pm) to make sure the wake-up peak does not reverse the increase in cortisol levels from the first to the second sample.



(a) ECG sensor. (b) PPG sensor.

(c) EDA sensor. (d) EMG sensor.

Figure 2: Sensors configuration.

2. STAI-S:

   State-Trait Anxiety Inventory ($STAI$) questionnaire comprises separate self-report scales for measuring two distinct anxiety concepts: trait anxiety ($STAI-T$) and state anxiety ($STAI-S$). Each scale is made up of 20 questions.
   The first one is to assess subjects' anxiety as a personality trait and is used, together with the $PSS4$, explained in section 4.1, for data interpretation.
   The second one measures anxiety as an emotional state linked to a particular situation. The $STAI-S$ is used as a subjective label after each phase together with cortisol levels to validate our protocol.

Since cortisol is considered to be a stress hormone, we expect cortisol levels to be higher in the second sample taken after the stress phase with comparison to the first one. $STAI-S$ scores should also be higher if the subject was indeed stressed in the second phase.

The combination of both physiological and subjective labels makes the validation process more reliable.

4.6 Dataset

Our dataset includes different types of parameters summarized in table 1 from 74 subjects, 38 women aged 19 to 63 years old (mean age: 33 y.o $\pm$ 12.5) and 36 men aged 21 to 79 years old (mean age: 35 y.o $\pm$ 13). Each parameter can be used either for data interpretation, classification or labeling depending on the end purpose. Some examples are presented but are not limited to table 1.

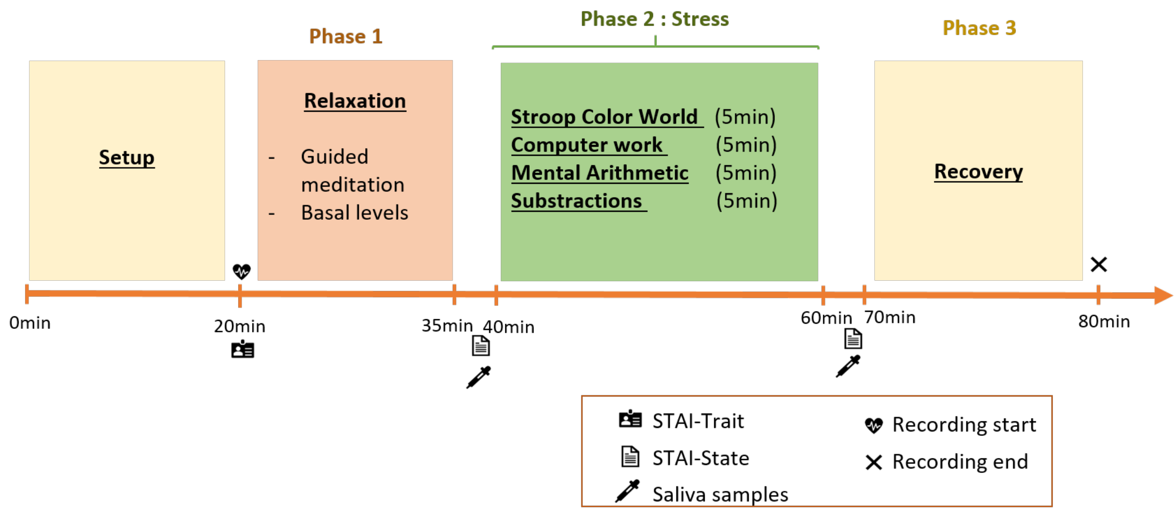


Figure 3: Study experimental protocol.

Table 1: Types and potential use of collected data.

Type	Data	Use
Profil Data	Sex,age ... Eating and sleeping habits Exercising Medidation	Interpretation
Subjective/Phsycological	PSS4 and STAI-T STAI-S	Interpretation Labeling
Behavioural	Responses Time Successes and failures in trials Task duration	Interpretation and/or segmentation
Physiological	Electrocardiogram (ECG) Photoplethysmogram (PPG) Electrodermal Activity (EDA) Electromyogram (EMG) Three axis gyroscope data **Salivary Cortisol Levels**	Data Analysis Classification Interpretation **Labeling**

The dataset features physiological signals such as ECG, PPG, EDA digitalised at $512Hz$ and EMG at $1000Hz$, as well as motion data from 74 subjects for a total duration of 40 minutes per subject, segmented in three sessions as explained in section 4.4. The first phase, *Relaxation phase*, is referred to as session 1, session 2 is the *Stress phase* and session 3 is the *Recovery*.

5 CONCLUSIONS

The experimental protocol presented in this paper takes into consideration many of the sources of variation encountered in previous studies. Its main purpose was to induce three states: relaxation, stress and neutral/baseline.

The study was carried out in a constrained environment and protocol validation was achieved using both psychological self-reports and ground truth cortisol levels which makes it reliable for machine learning algorithms. The dataset includes high-quality physiological modalities commonly used in commercial and medical devices for stress identification like ECG, PPG, EDA, EMG and three axis gyroscope data. Thanks to the high number of participant as well as their diversity in terms of age and gender, it is possible to draw reliable conclusions and statistical generalisation.

The dataset will be made publicly available once data cleaning and organisation are complete. It could be used in many different ways to study the correlation between various physiological signals with stress and/or stress recovery in a uni-modal or multi-modal approach. It could also be used to compare chest-based ECG device to earlobe PPG in terms of signal quality, prep-rocessing, and classification results. The self-reports could be utilized to create personalised models able to detect and predict a person's specific affective state.

ACKNOWLEDGEMENTS

Authors would like to thank Idex Sorbonne University for funding this experimental study as part of french state support for "Investissements d'Avenir' program". Also thanks to all the subjects and to INSEAD lab for their expertise in participant recruitment and management which made the process extremely easier.

ETHICS DECLARATIONS

All volunteers gave their informed written consent in accordance with the Declaration of Helsinki and following approval from and in accordance with the INSEAD Institutional Review Board (*IRB* : 202077).

REFERENCES

Adochiei, I., Adochiei, F., Cepisca, C., Seritan, G., Enache, B., Argatu, F., and Ciucu, R. (2019). Complex embedded system for stress quantification, 2019 (atee). *WOS: 000475904500049*.

Alamudun, F., Choi, J., Gutierrez-Osuna, R., Khan, H., and Ahmed, B. (2012). Removal of subject-dependent and activity-dependent variation in physiological measures of stress. In *2012 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*, pages 115–122. IEEE.

Bradley, M. M. and Lang, P. J. (1994). Measuring emotion: the self-assessment manikin and the semantic differential. *Journal of behavior therapy and experimental psychiatry*, 25(1):49–59.

Dalal, K. S., Chellam, S., and Toal, P. (2015). Anaesthesia information booklet: Is it better than a pre-operative visit? *Indian journal of anaesthesia*, 59(8):511.

Dickerson, S. S. and Kemeny, M. E. (2004). Acute stressors and cortisol responses: a theoretical integration and synthesis of laboratory research. *Psychological bulletin*, 130(3):355.

Fink, G. (2016). Chapter 1—stress, definitions, mechanisms, and effects outlined: lessons from anxiety. *Stress: Concepts, Cognition, Emotion, and Behavior; Fink, G., Ed*, pages 3–11.

Hart, S. G. and Staveland, L. E. (1988). Development of nasa-tlx (task load index): Results of empirical and theoretical research. In *Advances in psychology*, volume 52, pages 139–183. Elsevier.

Healey, J. A. and Picard, R. W. (2005). Detecting stress during real-world driving tasks using physiological sensors. *IEEE Transactions on intelligent transportation systems*, 6(2):156–166.

Kendler, K. S., Hettema, J. M., Butera, F., Gardner, C. O., and Prescott, C. A. (2003). Life event dimensions of loss, humiliation, entrapment, and danger in the prediction of onsets of major depression and generalized anxiety. *Archives of general psychiatry*, 60(8):789–796.

Koelstra, S., Muhl, C., Soleymani, M., Lee, J.-S., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A., and Patras, I. (2011). Deap: A database for emotion analysis; using physiological signals. *IEEE transactions on affective computing*, 3(1):18–31.

Koldijk, S., Sappelli, M., Verberne, S., Neerincx, M. A., and Kraaij, W. (2014). The swell knowledge work dataset for stress and user modeling research. In *Proceedings of the 16th international conference on multimodal interaction*, pages 291–298.

Schmidt, P., Reiss, A., Duerichen, R., Marberger, C., and Van Laerhoven, K. (2018). Introducing wesad, a multimodal dataset for wearable stress and affect detection. In *Proceedings of the 20th ACM international conference on multimodal interaction*, pages 400–408.

Schneiderman, N., Ironson, G., and Siegel, S. D. (2005). Stress and health: psychological, behavioral, and biological determinants. *Annu. Rev. Clin. Psychol.*, 1:607–628.

Schumm, J., Bächlin, M., Setz, C., Arnrich, B., Roggen, D., and Tröster, G. (2008). Effect of movements on the electrodermal response after a startle event. *Methods of Information in Medicine*, 47(03):186–191.

Tlija, A., Istrate, D., Gattoufi, S., and Bennani, A.-E. (2019). Stress recognition using connected devices: experimentation feedback. In *Journées d'Etude sur la TéléSanté*.

Ursin, H. and Eriksen, H. R. (2004). The cognitive activation theory of stress. *Psychoneuroendocrinology*, 29(5):567–592.

Van Steenis, H. and Tulen, J. (1997). The effects of physical activities on cardiovascular variability in ambulatory situations [ecg/accelerometry analysis]. In *Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society.'Magnificent Milestones and Emerging Opportunities in Medical Engineering'(Cat. No. 97CH36136)*, volume 1, pages 105–108. IEEE.

Warttig, S. L., Forshaw, M. J., South, J., and White, A. K. (2013). New, normative, english-sample data for the short form perceived stress scale (pss-4). *Journal of health psychology*, 18(12):1617–1628.

Yaribeygi, H., Panahi, Y., Sahraei, H., Johnston, T. P., and Sahebkar, A. (2017). The impact of stress on body function: A review. *EXCLI journal*, 16:1057.