Stress Detection Using Smartphone and Wearable Sensors

Seminar I

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Abstract

In Slovenia, the economic cost of work-related stress in 2009 was estimated to €1.2 billion, or approximately €1.300 per worker annually. In EU, the cost of work-related depression, which can be consequence of chronic stress, was estimated to €617 billion annually. Even though these estimates might be too pessimistic, they indicate the scale of the problem. A system for early detection of stress leading to appropriate counter-measures could improve many aspects of human life, including general health, education, economy and sports.

In this seminar, first, stress is defined using medical literature. Then, we present different approaches for measuring stress by reviewing the physiological signs analyzed in studies for stress (e.g., heart rate, sweating rate, skin temperature, etc.), as well as psychological questionnaires used for assessing stress. Next, we present critical overview of the existing methods on stress detection, focusing on studies that use smartphone and/or wearable sensor in combination with voice analysis and/or bio-signal analysis. We point out the pros and cons for each one of them, giving accent to accuracy, obtrusiveness and the possibility for using them in a real-life scenario. The focus in the literature slowly shifts from stress detection in laboratory conditions using intrusive sensors, to stress detection in real-life conditions using unobtrusive sensors. After summarizing the potential drawbacks of the reviewed stress detection methods, we propose a machine-learning method for real-life unobtrusive stress detection by integrating three modules (smartphone sensors, physiological sensors and voice analysis), which hopefully will be able to overcome the problems of individual methods and offer better performance than any of them. Finally, two scenarios for collecting of training data are proposed, one real-life and one in laboratory conditions.

Keywords: stress detection, smartphone, physiological sensors, wearable sensors, voice analysis, machine learning.
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1. Introduction

Stress is a process triggered by demanding physical and/or psychological tasks. It is not necessarily a negative process, but under certain conditions the stress process results in chronic stress which have negative consequences. For example, when human undergo vigorous physical activity (e.g., intense training, competitive sports match, etc.) the body is presented with large (mainly) physical stressor, invoking response of the sympathetic nervous system to meet the increased metabolic demands. In the most basic sense, the sympathetic nervous system acts to speed up certain processes within the body (“fight-or-flight” response) [1]. In this scenario, the sympathetic nervous system is responsible for raising the heart rate, increasing blood pressure, increasing glucose concentration in the blood (to fuel activity), etc. After the demanding physical activity, the sympathetic nervous system slows down, and the parasympathetic nervous system drives the rest and repair processes to get things back to normal. Ideally, these two nervous systems (sympathetic and parasympathetic) remain balanced in their efforts. If the balance is not maintained (e.g., the body experience the stressor too often), and the activation of the sympathetic nervous system is constantly higher throughout a longer period, the likelihood of fatigue and overtraining is greatly increased. This is the part when the stress process can have negative influence on the body, since overtraining can result in mood changes, decreased motivation, frequent injuries and even infections [2].

Similarly, instead of athletes dealing with physical work-load, we can analyze students or workers dealing with psychological or mixture of psychological and physical work-load. In this case, if the sympathetic-parasympathetic (“yin-yang”) balance is not maintained and occupational stressors (e.g., stressors: meetings, exams, deadlines, etc.) are present for a longer period, chronic occupational stress can be triggered. Chronic occupational stress produce negative consequences such as raised blood pressure, bad sleep, increased vulnerability to infections, slower body recovery processes [3], and overall decreased mental performance. To prevent chronic occupational stress from showing at first place, daily stress monitoring systems can be exploited (“prevention is better than cure”), which is the idea of this seminar.

Regarding the negative consequences of stress (e.g., mental illness, depression), the USA’s National Alliance on Mental Illness via survey [4] revealed that 64% of the students who drop out of college do so for mental health reasons. In 2013, the cost to Europe of work-related depression was estimated to €617 billion annually [4]. In Slovenia, the economic cost of work-related stress in 2009 was estimated to €1.2 billion, or approximately €1.300 per worker annually [6]. Therefore, a system for early detection of stress leading to appropriate counter-measures could improve many aspects of human life, including general health, education, economy and sports.

Our research is based on the definition of stress by Ice and James: “Stress is considered a process by which a stimulus elicits an emotional, behavioral and/or physiological response, which is conditioned by an individual’s personal, biological and cultural context” [7]. Figure 1 illustrates the stress process. Stressors are defined as stimuli which elicit a response; mediators and moderators affect one’s appraisal of stressors and influence the emotional, behavioral and physiological responses; appraisal determines which potential stressors result in stress response. All components of the stress response influence one’s physical and mental health.

To develop an unobtrusive stress detection system, we focus on monitoring the stress response, including its three components (emotional, behavioral and physiological).
2. Measuring stress

In studies for automatic stress detection, it is necessary to have an objective stress measure for evaluating the results achieved by a proposed approach for stress detection. This objective measure is called ground-truth. The purpose of the ground-truth is to provide a quantification of stress which the system models. In the following subsections we will overview methods for measuring stress used in medicine, psychology and computer sciences.

2.1 Measuring stress in medicine and psychology

The medical method for measuring stress includes monitoring levels of stress hormones (e.g., cortisol) using blood, saliva, urine samples, or saliva enzyme analysis [8] [9]. These methods produce accurate stress measures, but require expensive medical equipment and long analysis conducted by medical specialist, therefore are unsuitable for studies in computer sciences as well as studies where several daily stress measures per subject are needed.

In psychology, the most exploited method for assessing mental stress is using questionnaires. The simplest approach is by asking the subjects’ to rate themselves on a predefined stress scale. This method measures perceived stress level, and its main drawback is subjectivity. To obtain more objective stress measure, more complex questionnaires are used. The idea behind the questionnaires is that the amount of stressors in a person’s life often (although not always) correlates with the amount of stress that person experiences. Such questionnaires are verified on specific population, and a statistical significance is provided using comparison to physiological measurements (e.g., cortisol levels). These questionnaires assess long-term stress, containing questions such as: “In the last month, how often have you felt that things were going your way?”[23]; or short-term stress e.g., Daily Stress Inventor questionnaire [24] - which provide measure of daily level of minor stress, and “PANAS” scale [25] - which provides measure for positive and negative affect. The drawback of the stress questionnaires is their intrusiveness (usually the subjects need to answer 10, 20 even up to 50 questions), and subjectivity. However, usually the stress questionnaires (even simple question as “How stressful was your day”) are the best choice for scientists (especially in computer science studies) when subject’s effort and economic costs are taken into account.
2.2 Measuring stress in computer science studies

In computer science studies, to overcome the problems of the medical methods for measuring stress, arising due to lack of time, medical experts, medical equipment and economic costs, usually physiological signs (e.g., heart rate, sweating rate, etc.) are combined with questionnaires to provide ground-truth for automatic stress detection systems. Sometimes, the physiological signs are used as an input data to a system for automatic stress detection, and the ground-truth is obtained using only questionnaires [34]. Clear boundary about which physiological sign is used as an input variable and which as a ground-truth variable, cannot be stated. It depends on the goal and focus of the study. For example, if a study presents an approach for stress detection using voice analysis, then stress questionnaires and physiological signs can be used for obtaining ground-truth for assessing the level of stress (e.g., low, medium and high) [43].

The physiological signs monitored in stress studies are: electrocardiography (ECG) signal - representing heart activity; galvanic skin response (GSR) signal, also known as electrodermal activity (EDA) signal - representing sweating rate; blood volume pulse (BVP) signals - representing the volume of blood that passes over a photoplethysmographic sensor with each pulse [10]; blood pressure signal - representing the pressure exerted by circulating blood on the blood vessels; electroencephalography (EEG) signals - representing brain activity; electromyography (EMG) signals - representing muscle activity; skin temperature, and respiration rate.

Heart Rate

It is well known that a stressful situation is usually accompanied by an increased heart rate, as a part of the “fight or flight” response of the body. However, the increased heart rate is only a temporary sign and gives very little (if any) information for the overall stress that the body experiences. Besides heart rate as a raw information, the most exploited approach in stress studies is Hear Rate Variability (HRV) analysis. HRV measures the amount of variability of the time between heartbeats. An average heart rate of 60 beats per minute does not mean that the interval between successive heartbeats would be exactly one second, instead they may vary. HRV is proven method for assessing human health in laboratory conditions [10][11][13]. It offers a glimpse into the activity of our autonomic nervous system. "Too little variation indicates age-related system depletion, chronic stress, pathology, or inadequate functioning in various levels of self-regulatory control systems." [14]. With the advancement of the wearable sensors the HRV analysis can be exploited in real-life studies for stress detection. Also, on the market exist smartphone applications that offer HRV analysis using chest-strap HR monitor, e.g., “Elite HRV” [15] and “CardioMood” [16]. The main problem when using HRV analysis for unobtrusive stress detection is how to extract accurate HR signal, since the wearable sensors are prone to measurement errors caused by movement, noise, calculations, etc.

Galvanic Skin Response

Galvanic skin response (GSR) is another physiological sign that significantly correlates with stress [19] [29] [31]. So far, this correlation has been studied mainly in controlled environment. The latest technical advancement in wearable sensors offers devices for unobtrusively measuring GSR throughout the day [16]. Unfortunately, there are numerous factors that influence the GSR besides stress (e.g., physical activity, eating, increased room temperature etc.). In future, the link GSR-stress should be analyzed in real-life conditions and solutions should be proposed to distinguish the different causes for GSR variations.

Blood Volume Pulse

Until recently, obtrusive devices were used for obtaining continuous blood volume pulse (BVP) measures. Usually these devices were placed on the subject’s ear or finger, disallowing normal function during real-life activities. The latest technical advancements allow unobtrusive BVP measures using wrist-worn watch-like sensor (e.g., Empatica E3 [17]). The BVP signal can be directly used for stress analysis since previous studies have shown correlation between BVP (measured on subject’s finger) and different stress levels [18][19]. The BVP measures can be also used for extracting HR signal and then HRV analysis can be performed [17]. However, the same constrains are applied here, extracting accurate HR signal from BVP signal, is subject to many errors due to movement, noise and calculations.
Blood Pressure
Another approach for monitoring stress levels is by monitoring blood pressure throughout the day. “Blood pressure changes to meet actual or perceived physiological need, which may or may not adapt people to their surroundings. The constant change in blood pressure is what makes it a useful stress measure” [7]. The downside of this approach is that the subject needs to wear blood pressure monitor throughout the day (since dozens measures need to be taken per day) in order to provide enough measures for analyzing stress levels.

EEG Signal
EEG signals provide valuable information for the overall human state by offering glimpse into the brain’s activity. Regarding stress, Dharmawan used EEG signals for analysis of stress level while the subjects were playing computer games [20]. However, the EEG signal analysis is not suitable for real-life unobtrusive stress detection mainly because the subject need to wear device (e.g., Emotiv EPOC headset [21]) on his head for obtaining EEG signal.

Other Physiological Signals
EMG, skin temperature and respiration rate are physiological signs often included in stress studies. However, these physiological signs have been proven to be less effective compared to HRV or GSR analysis for stress detection in real-life scenario [31].

In a recent study-survey [22], Sharma et al. performed an empirical ranking of measures for stress. The results are summarized in Table 1. The ranking is based on correlation with stress claimed in literature, equipment intrusiveness, techniques developed for mapping to stress scales, and extent of usage in the literature. The top three physiological measures for stress are HRV, GSR and EEG. Blood pressure, skin temperature, BVP, and respiration rate, are in the lower part of the ranking list. The measures pupil diameter, eye gaze and facial expression are highly ranked by the authors, but these measures require serious video analysis, and are out of the scope of this seminar. Also, voice is usually used as a signal for detecting stress, and not for measuring stress (as a ground-truth). The last ranked measure (not presented in the table) is EMG, confirming the fact that EMG signal is less preferred than the other physiological signs.

Table 1. Sharma et al. [22], empirical ranking of measures for stress based on correlation with stress claimed in literature, equipment intrusiveness, and techniques developed for mapping to stress scales

<table>
<thead>
<tr>
<th>Rank</th>
<th>Measure</th>
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<tbody>
<tr>
<td>1</td>
<td>Hear Rate Variability (HRV)</td>
<td>7</td>
<td>Facial Expression</td>
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<tr>
<td>2</td>
<td>Galvanic Skin Response (GSR)</td>
<td>8</td>
<td>Blood Pressure</td>
</tr>
<tr>
<td>3</td>
<td>Electroencephalography (EEG)</td>
<td>9</td>
<td>Skin Temperature</td>
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<tr>
<td>4</td>
<td>Pupil Diameter</td>
<td>10</td>
<td>Blood Volume Pulse</td>
</tr>
<tr>
<td>5</td>
<td>Voice</td>
<td>11</td>
<td>Eye Blinks</td>
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<tr>
<td>6</td>
<td>Eye Gaze</td>
<td>12</td>
<td>Respiration</td>
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</tbody>
</table>

3. Related approaches for stress detection
When analyzing approaches for stress detection, two main characteristics has to be considered: how ground-truth is obtained (which was discussed in the previous section), and the “type” of stress that is analyzed - either it is induced stress or real-life stress. Stress can be induced using some kind of stress test [26] or stress inducing game [39]. When using stress inducing task, it is often assumed that the more intense the task, the higher stress level it induces, simplifying the determination of the ground-truth. Also, in studies analyzing real-life stress, the uncontrolled environment is additional problem besides the determination of the ground-truth.

The following section provides literature overview through the prism of computer science and engineering. Moreover we are analyzing approaches that use physiological sensors (e.g., GSR, HR, skin temperature etc.), voice analysis or smartphones. Besides these three, also brain activity analysis [20], video analysis (e.g., facial expressions, pupil diameter) [27][28] and smart keyboard/mouse [29] are proposed in the literature.
3.1 Stress detection using physiological signs

Stress detection using physiological signs is the most exploited approach in the literature. The focus slowly shifts from stress detection in laboratory conditions using intrusive sensors to stress detection in real-life conditions using unobtrusive sensors.

Sierra et al. [29] proposed person-specific template based approach for stress detection. They model the behavior of individuals under stressful and non-stressful situations and create a stress template by gathering physiological information. The galvanic skin response and heart rate are measured during laboratory stress inducing test which includes hyperventilation and talk preparation. They compared several approaches: Gaussian mixture model, k-Nearest neighbor, Support vector machines and Fuzzy logic. All approaches achieved over 90% accuracy. The highest accuracy of 99.5% is achieved by user-specific models using fuzzy logic. This study confirms that stress induced in laboratory environment, can be detected almost perfectly using galvanic skin response and heart rate signs. It would be interesting to try similar approach, where for each subject a stress-template is extracted in controlled environment, and later that stress-template is used in real-life for person specific stress detection.

Healey and Picard [31] presented another quite accurate stress detection system, achieving 97% accuracy, which is tested in a semi-controlled real-life scenario (while the subjects are driving a car). The downside of this approach are all the physiological sensors used, namely: electrocardiogram (ECG); electromyogram (EMG); skin conductivity (measured both on hand and foot); and respiration. Even though the presented system is obtrusive, it conforms that stress detection is possible in real-life scenario.

Wijsman et al. [32] used ECG, respiration rate, GSR and EMG, measured with a wearable system during stress inducing test in office-like laboratory scenario. The average accuracy for two class problem was 74.5%. Even though the proposed monitoring system is obtrusive, this study presents valuable information for monitoring stress in office-like scenarios.

Hernandez et al. [33] monitored nine employees in a call center using wrist-worn GSR sensor for a week, and used stress level self-reports to label each call. The achieved accuracy for person-specific models is 78%, and 58% for general models. They manage to improve the accuracy of the general model to 73% using adaptations of the SVM classification algorithm. This study shows that user-specific models are more accurate for stress detection, especially when self-reported ground-truth is used. However, some adaptation can be implemented in order to improve the accuracy of general models.

Recently, Muaremi et al. [34] presented a real-life study for stress detection using two wearable devices, one chest-strap monitor and one wrist-worn device. They used physiological signs such as ECG signal, respiration, body temperature and GSR signal, and information such as upper body posture and accelerometers on the body and arms. The ground truth is obtained by asking the subjects the following two questions: How stressed have you felt today? (from 0 to 1); How stressed have you felt today compared to yester- day? (from -1 to +1). General models are built, with the best achieved accuracy of 73 % for a 3-class problem. Regarding the fact that the subjects are monitored only at night, the achieved accuracy seems promising. It would be interesting for this approach to add daily stress analysis.

Ramos et al. [35] analyze stress induced in laboratory conditions, but unlike the other similar approaches in this study the subjects perform three different activities (cycling, walking and sitting). They recorded data for heart rate, breathing rate, skin temperature and acceleration and GSR, using chest-strap sensors and arm band sensors. For two class problem, they manage to achieve f-measure of 69%. This study provides valuable insights into stress detection under different physical activities which should be taken to a next level by stress detection completely outside the lab and using unobtrusive sensors.

One study indirectly related to stress [36], analyzes GSR activity during different sleep stages in order to provide relations between the sleep stages and GSR. Such serious sleep analysis, providing information about the sleep stages using unobtrusive GSR sensor, certainly can be beneficial for a stress detection system since sleep disturbance is highly correlated with stress [37].

In another study [38], the authors used GSR signal recorded with two electrodes attached to the subject’s hand. Subjects took part in a mathematic test used to induce stress. This study focuses on filtering methods for analyzing GSR signals, which are extensively used in stress detection studies.
3.2  Stress detection using voice analysis

Besides using physiological signs, another approach for stress detection uses voice analysis, which is totally unobtrusive approach, but subject’s privacy should be considered.

In study presented by Scherer et al. [39] fifteen subjects were asked to play stress inducing game. While playing, the subjects were asked to verbally answer some questions. The answers were recorded and then labelled for stress levels by a different set of subjects, which heard the recordings in random order without visual information. The ground-truth for each recording is a mean of all the labels for the particular recording. Neural network model was trained and tested using 10-fold-cross validation. The results shows that the neural network performed better (better mean absolute error and mean square error) than the best human labeler when predicting the ground-truth label. This approach confirms that stress can be detected in controlled environment by analyzing subject’s voice using machine learning approach. In particular echo state neural network is used. However, it would be interesting to test the approach using leave one out cross-validation and in real-life scenario.

Demenko et al. [40] presented stress voice analysis done on authentic police emergency phone calls. The calls were manually selected and annotated. They concluded that extreme stress can be recognized with 80% accuracy.

Aguilar et al. [41] collected physiological data, voice data and questionnaire data in a scenario where the subjects’ were taking an exam. The annotated speech is freely available on the net [42], and can be used for developing methods for voice based stress detection.

3.3  Stress detection using smartphones

The development of smartphones and their continuous technical improvement has significantly contributed to stress detection using smartphones.

“StressSense” [43] detects stress using speech cues from dialogues recorded and analysed using smartphones. They studied stress associated with cognitive load experienced during a job interview, and conducting a marketing task as an employee. GSR sensor is used for ground-truth purpose. For two class problem, using model adaptation, “StressSense” achieved accuracy of 81% in indoor, and 76% in outdoor environment. Even though the smartphones were attached to the subjects (outdoor scenario), and placed in front of the subjects (indoor scenario), making it difficult to use the approach in real-life, the study confirms that voice-analysis can be done using Android phones in real-time.

Bauer at al. [44] presented a study on seven subjects where smartphones (GPS, Wi-Fi, Bluetooth, Call and SMS analysis) are used to detect stress related changes. Subjects were monitored during a two week exam session (stressful period) and the two following weeks (non-stressful period). Their conclusion is that regarding the stressful and non-stressful period, behavior modification can clearly be seen, however, the exact interpretation and generalization requires larger study. Although not exactly stress detection, this study confirms that smartphones can be used to detect behavioral changes.

“MoodSense” [45] is a study by a Microsoft Research Group in Asia. They tried to infer user’s mood using six pieces of usage information (SMS, email, phone call, application usage, web browsing, and location). Their conclusion is that mood inference should be personalized since the general model mixes even the extremes of the discrete mood states (“very positive” and “very negative”). Also, per-feature analysis showed that different features are more valuable for different users, meaning it is hard to obtain general feature set for mood detection using only smartphones.

In the “StudentLife” study [46] the authors used automatic sensing data from smartphones to assess students’ mental health, activity level, sociability, academic performance, and behavioral trends. Their approach is based on correlation analysis between different aspects of the students’ life. One of the main conclusions of that study is: “Results from the StudentLife study show a number of significant correlations between the automatic objective sensor data from smartphones and mental health and educational outcomes of the student body”. In our previous work [48] we tried to take the findings of the StudentLife study one step further by implementing a machine-learning method to detect the students’ perceived stress levels. We used their data (data of the StudentLife study), which is freely available on web [47]. The goal was to develop a machine-learning model that can unobtrusively detect the stress level in students using data from several smartphone sources: accelerometers, audio recorder, GPS, Wi-Fi, call log and light sensor. From these, features were constructed describing the students’ deviation from usual behavior. Our conclusion was that perceived stress is very subjective and each individual is specific, so smartphone stress detection based on behavioral analysis can be performed by building person-specific models, where certain period of time
(e.g. 20-25 days) user input is needed. The person-specific models achieved accuracy over 60% for a 3 class problem, which is comparable results with existing studies on stress detection using only smartphone data.

3.4 Stress detection using combination of smartphone and physiological signs

In the literature exist several studies where combination of wearable sensors and smartphones is used.

Phil Adams et al. [48] analysed minimally intrusive stress detection in real-life environments. In their study, data is collected from seven participants as they carried out their everyday activities over a ten-day period. They used smartphone audio-sensing and wrist-worn GSR sensor. They analyzed correlations between stress self-reports, smartphone audio-sensing and GSR activity. They concluded that the main drawback of GSR approach is that “it is statistically impossible to detect from GSR data alone the valence of the perceived stress response, that is, whether increased arousal is associated with pleasant experiences or the negative experiences”. Also, they concluded that, correlation between stresses self-reports and voice-stress detection exist at presence of a clear voice signal; stressful situations in which vocalizations are not present cannot be inferred at all. In future, solutions should be proposed about how to distinguish arousal caused by positive and arousal caused by negative experiences, and solutions to obtain subjects’ clear voice signal.

Sano et al. [50] used smartphone data in combination with a physiological sensor for stress detection in real-life environments. They collected 5 days of data for 18 participants using a wrist-worn sensors (accelerometer and GSR) and smartphone (calls, SMS, location and screen on/off). As a ground-truth, self-reports are used. They applied correlation analysis to find statistically significant features associated with stress, and used machine learning to classify whether the participants were stressed or not. The reported accuracy for a 2 class problem is over 73% by using 10-fold cross-validation. In their approach the wrist-worn accelerometer data is not used for distinguishing GSR caused by physical activity or stressful event. This can be done in future work for improving the accuracy of such system.

Similarly, in another study [51], combination of GSR sensor and smartphones is used for stress detection in real-life environments, where the ground-truth is self-reported. They concluded that if the data from the GSR sensor is removed and only smartphone data is used, the accuracy for a three-class problem drops from 61% to 55% for user-specific, and from 53% to 45% for leave-one-out cross-validation. These results indicate how challenging is the problem of detecting stress by using only smartphone data.

4. Proposed approach for stress detection

Revising the related work, the following conclusions can be made, which are relevant for the approach that we are proposing for real-life unobtrusive stress detection:

- Analysis of physiological signs can produce the most accurate results in stress detection, especially using HR signal, heart rate variability and galvanic skin response.
- In controlled laboratory environment, person-specific models can recognize induced stress using HR and GSR information, with accuracy up to 99.5% [30].
- In controlled environment (driving a car), using physiological signs, real-life stress can be recognized (especially if ground-truth is well defined) with accuracy up to 97% [31].
- In real-life, using only physiological data, it is hard to distinguish arousal caused by positive and arousal caused by negative experience [49].
- In real-life, using voice analysis, heavy stress can be recognized in phone call conversation [40], however in everyday scenario obtaining recording during stressful event is challenging [49].
- In real-life, smartphones, as only source of information, are not the best choice for stress detection, since much better results are achieved using physiological signs or voice analysis. However, smartphones can be used for detecting changes in subjects’ behavior, which can be valuable input to a system for stress detection.

To tackle the problems that arise when trying to detect real-life stress in uncontrolled environment, we plan to use several sources of information which, hopefully combined can overcome the shortcomings of the individual approaches. Figure 2 shows the proposed approach for unobtrusive stress detection. The idea is to automatically monitor all three components of the stress response, namely emotional, physiological and behavioral response.
For the **emotional** response, smartphone microphone will be used along with emotional voice analysis. The subjects occasionally record an audio message, or some of their phone calls can be analyzed while respecting their privacy (e.g. on-the-fly voice analysis which extracts features from the audio recording without saving the actual recording). The voice analysis focuses on the emotional state of the user, and not directly on the stress level, since detecting low stress levels is a challenging task, and if we focus only on stress detection then valuable information (the emotional state of the user, which should be easier to obtain from a clear recording), will be lost.

For the **physiological** response, a wrist-worn device can be used to provide readings of the subjects physiological signals (e.g. blood volume pulse, sweating rate, heart rate, skin temperature, etc.). To extract features from the subject’s physiological signs, tools for bio-signals analysis can be used [52].

For the **behavioral** response, data from the smartphone sensors (accelerometers, light sensor, GPS, Wi-Fi, etc.) and smartphone usage can be extracted.

All the features extracted using voice analysis, bio-signal analysis, smartphone sensors, and smartphone usage analysis, can be combined to extract useful high level information which can be real-time information (e.g. emotional state, physiological state, location, activity, ...) or general information (e.g. sleep hygiene, energy expenditure,...). Finally, the high-level information can be used to detect real-time stress and overall daily stress levels.

![Diagram](image)  
**Figure 2. Proposed approach for unobtrusive stress detection.**

The proposed machine-learning method for unobtrusive stress detection by monitoring three components of the stress response (emotional, behavioral and physiological) is in line with the medical theory behind stress. Integrating all three approaches into a single multimodal stress detection system has – to our knowledge – not been done before. We hope it will be able to overcome the problems of individual approaches and offer better performance than any of them.

### 5. Data collection

For each machine-learning approach, first of all a data is needed for developing, analysis and evaluation of the proposed approaches. In the following we will explain two data-collecting scenarios, one real-life scenario and one laboratory scenario. In the laboratory scenario data will be collected while stress is induced using stress inducing test or game. The purpose of the laboratory scenario is efficient data collecting which will be used for developing draft versions of the machine learning approach which later will be analysed, tested and improved with the real-life scenario.
5.1 Data collecting – real-life scenario

The ideal scenario for collecting of training data would be mimicking the real-life scenarios in which the system for unobtrusive stress detection would be used. Since we are aiming to detect stress during everyday activities, special scenario is not needed. The only thing that needs to be defined is what should be monitored and what should be labeled during the everyday activities. Regarding the monitoring, the subjects will wear wrist-worn device (Figure 3) and a smartphone. The wrist-worn device is equipped with physiological sensors (monitoring heart rate, sweating rate, blood volume pulse, accelerometers and skin temperature). This device will collect data 24/7 (if worn). The smartphone also will collect data using all of its sensors, it will provide statistics about smartphone usage (calls per day, duration, SMS, etc.) and will be used to gather audio data.

Regarding the labelling of the data, the subjects will need to label (and rate) each stressful event in their life; to rate the overall stressfulness of the day; and to label certain events that influence the physiological signs (exercise, caffeine and alcohol).

5.2 Data collecting – induced stress scenario

The proposed scenario for data collecting in the real-life scenario can last for several months (monitoring at least 10 subjects during a period of at least two weeks), especially if small number of wrist-worn devices and smartphones are available. A solution for a quick start is needed in order to allow developing of draft version of the system. For that reason we propose a laboratory scenario where stress is induced, the subjects are monitored with the same physiological sensors that will be used in the real-life scenario, and audio data will be recorded using smartphones while the subjects verbally answer questions. The data collected in laboratory scenario doesn’t directly allow us to analyze the proposed approach for real-life unobtrusive stress detection, but it can be beneficial for the following reasons:

- Efficient collecting of stress labeled data for 10 people in 2-5 days;
- Building a draft machine-learning method for emotion (and/or stress) detection by voice analysis.
- Building a draft machine-learning method for stress detection using physiological signs.
- Creating a stress template – the idea behind extracting a stress template is from the study by Sierra et al. [29], where they model the behavior of individuals under induced stressful and non-stressful situations, and create a stress template by gathering physiological information (heart rate and sweating rate). We plan to use the induced stress scenario to construct person-specific stress template which later will be used in real-life scenario for stress detection.

![Empatica E3 device equipped with physiological sensors](image)

Hopefully, at the end, the data collected using the two proposed scenarios (real-life and laboratory scenario), will allow developing of the proposed machine-learning approach for real-life unobtrusive stress detection.
References


