UNIVERSITÀ DEGLI STUDI DI BARI ALDO MORO

DIPARTIMENTO DI INFORMATICA

PhD Program in Computer Science and Mathematics
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Research Project

PhD Student: Daniela Girardi

Supervisor: Prof. Filippo Lanubile
Co-supervisor: Dott.ssa Nicole Novielli

Coordinator: Prof. Maria F. Costabile

PhD student signature

Supervisor signature

Co-supervisor signature

1. Research title: Sensor based emotion detection

2. Research area:

Affective Computing, Human Computer Interaction, Software Engineering, Assistive Technologies

3. Research motivation and objectives

A. Research Goal

The goal of this research is to investigate whether it is possible to predict emotions accurately by measuring physiological signals through noninvasive and low cost biometric sensors. We first aim at investigating what are the most relevant physiological measures to define the optimal combination of sensors for both valence and arousal. Second, we plan to apply emotion recognition into characteristic scenarios in the domain of assistive technologies and software development.

B. Motivation

Affective computing [45] has become an established discipline concerning the study, design and implementation of systems able to recognize and simulate human affect, i.e. emotions, opinion, interpersonal stances, personality traits [51]. Specifically, emotion detection can be used to identify cognitive or anxiety disorders as well as situations of stress and frustration [41]. This is very relevant in the health domain [3] as well as in work environments, where negative emotions can negatively impact performance [1].

As regards the e-health domain, specifically assistive technologies, information about the emotional state can be exploited by the medical staff to adjust the treatment accordingly. Emotions felt by patients during or after a rehabilitation session could be an indicator of how the treatment is going on. In fact, psychologist studies affirm that it is necessary to adapt the treatment depending on emotional feedback of the patients [19][20][28]. However, especially in cases where the brain is seriously damaged, people might not be able to speak, express their needs and feelings. So, patients cannot reveal directly their emotions.

As regards the work environment, early detection of emotional states may enable monitoring of employees' wellbeing so as to avoid burnout [35]. In particular, in the field of software development, monitoring emotional state of developers might be used to assess whether a developer is currently stuck or frustrated and react accordingly [55]. In case of detection of negative affective states, developers could be supported by suggesting them to take a break or preventing them to introduce bugs into code [41]. In addition, to alert in time the team leader or colleagues when someone is working unwillingly might be useful to discover if an unfair subdivision of tasks has been done. Causes of stress and frustration could be related to the content of activities which developers have to conduct, sometimes repetitive and boring, and to temporal aspects such as insufficient time to complete activities before the established deadline [22][25].This is in contrast with the Agile methodology, that nowadays is substituting the traditional waterfall model of software development. In fact, one of the principles behind the Agile manifesto says: "Agile processes promote sustainable development. The sponsors, developers, and users should be able to maintain a constant pace indefinitely."[46]. So, discover if developers are tense could be an indicator of incorrect application of Agile manifesto. In addition, recent studies highlighted a correlation between programmers' emotions and progress during software development tasks [41]. Specifically, experiencing positive emotions leading to more progress [7], while the state of being stuck and making no progress leading to frustration [8].

Recent approaches to emotion recognition successfully adopt sensors with multiple channels for capturing biofeedback. Monitoring electrical activity of the brain electroencephalography (EEG), and physiological signals such as electrodermal activity (EDA), and heart rate (HR) is a way to get information about emotional state of people. Changes in the body, in fact, are strictly related to emotions [9][27][32][34][53]. It is the case, for example, of EEG helmets using from 32 to 60 electrodes for capturing the brain activities [33][43][52]. Nowadays, wearable technology makes possible measuring these signals using noninvasive low cost biometric sensors [21] in order to understand emotions felt, without an explicit explanation or risking to misinterpret other signals such as facial expressions, tone of voice and gestures.

4. State of the art

Psychologists worked at decoding emotions for decades, focusing on how to classify them, what is their functioning, and what is the role played by cognition in their triggering [11]. Multimodal emotion recognition can rely in difference sources of information that can be leveraged in automatic approaches: facial expressions, speech and prosody, body movements, natural language, biometrics. As for biometrics, thanks to advance of wearable technology is it possible to detect emotions using noninvasive, off the shelf, biometric sensors, such as headsets and bracelets. These devices record body responses to stimuli, as typically happens when emotional states are triggered by an event, a picture, a video, and so on. In the following, we report state of the art related to two different scenarios we want to explore.

A. Emotions and physiological measures

Emotion recognition from biometrics is a consolidate research field that is relevant to a wide range of application domains, from human-computer interaction [34] to healthcare [3] and software engineering [41][54]. Some of the most commonly physiological measures can roughly be categorized into eye-related, brain-related, skin-related measures or heart-related [18].

Eye-related. There is a variety of eye-related measures, such as the pupil size, fixation duration or number of saccade. Saccade is a quick, simultaneous movement of both eyes between two or more phases of fixation in the same direction [12]. Research shows that pupil size and fixation duration is affected by positive and negative emotions [10][39][40].

Brain-related. Electroencephalography (EEG) records electrical activity of the brain through electrodes placed on the surface of the scalp. Cerebral waves can be categorized based on frequency as delta, theta, alpha and beta waves. In particular, delta waves are recorded mainly during sleep, theta waves indicate a decrease of vigilance level, alpha waves are recorded during relaxing moments, especially when people close eyes and beta waves instead are observed during mental processes, such as attention or concentration or when people feel anxious [38].

Skin-related. Electrodermal activity (EDA), also known as Galvanic Skin Response (GSR) or Skin Conductance (SC), is a measure of the electrical activity of the skin due to the variation in human body sweating. EDA varies consistently with intensity of emotions: more evident changes can be notice for emotion with high arousal [5].

Heart-related. Heart Rate (HR) is the number of contractions of the heart (*beats*) each minute. The variation in time interval between heartbeats is called Heart Rate Variability (HRV). Heart Rate is usually measured using Electrocardiography (ECG). However, this measures can be obtained in a less intrusive way, based on Blood Volume Pulse (BVP), that is, the volume of blood that passes through the tissues in a localized area with each beat (pulse) of the heart. BVP measurement is obtained by the use of a photo plethysmography (PPG) sensor. In [4], authors found that heart rate slows down when people feel negative emotions.

B. Emotion Awareness in Assistive Technologies

One of the main challenges in the healthcare domain is helping the victims of accidents or diseases to recover as close as possible their regular lifestyle. Today technology represents a valid support for rehabilitation, especially focusing on virtual reality and videogames.

In [48] Rivas et al. describe “Gesture Therapy”, a system that allows users to do some rehabilitation movements while they are playing videogames. Mental state of patients is monitored using motion and pressure from the affected limb, in order to optimize the therapy outcome, automatically adapting the game to the different patients changing needs.

Hou et al.[29] developed a multi-level computer game, “Basket”, following the traditional rehabilitation exercise that consist of putting different objects into the basket. During the game, they monitor the patients emotions through an EEG headset to adapt the game level accordingly.

In Matteucci et al. [36], the authors show that it is possible to discriminate up to five levels of stress and adapt the rehabilitation process to the patient needs with the goal to reduce frustration and improve interest as well as to give useful feedbacks to therapists.
They have measured biological signals such as skin conductance, blood volume pressure, respiration rate and electrical activity of muscles.

Palaska et al. [44] distinguish whether the subject is under-challenged or over-challenged using psychophysiological signal data collected from biofeedback sensors while executing the tasks with RehabRoby. It is a device that provides active motion assistance and is able to produce shoulder flexion/extension, shoulder rotation, elbow flexion/extension and forearm pronation/supination upper extremity movements. They conducted the study to give a contribute for robot-assisted rehabilitation systems that can modify the rehabilitation task based to better suit patients ability.

Appel et al. [2] developed a supervised artificial neural network that interprets facial infrared thermal images of individuals performing rehabilitation robotic therapy integrated with games. They aimed to find noninvasive and nonverbal techniques to classify emotions, especially for patients who have speech capacity compromised due to cerebrovascular accidents. They classified between three categories of emotions (neutral, motivated, overstressed).

C. Emotion Awareness in Software Engineering

Emotion awareness in software engineering is a topic that is receiving increasingly attention among social aspects of software engineering[1]. Indeed, affective states such as personality traits, attitudes, moods, and emotions play a crucial role on people’s everyday performance at work. In particular, IT professionals as software developers experience a wide range of emotions in their work [16][23][42]. In fact, software development is a mainly intellectual activity, requiring creativity and problem-solving skills that are known to be influenced by affective states [1].
The correlation between mood and programmer performance has been studied for the first time in a controlled experimental setting by Khan et al. [31] . They performed two experiments to investigate the relationship between emotions and performance of software developers: in the first one, they have induced emotions through video clips observing that them had a significant effect on programmers debugging performance; especially, they found a significant difference after observing low- and high-arousal. In the second experiment, programmers’ mood was manipulated by asking participants to dry run algorithms for at least 16 min. Participants performed some physical exercises before continuing dry running algorithms again. The results showed a significant increase in arousal and valence that coincided with an improvement in programmers task performance after the physical exercises. The final conclusion of this study is that programmers’ moods influence some programming tasks such as debugging.

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[1] See the workshops series on Emotion Awareness in Software Engineering co-located with ICSE, the International Conference of Software Engineering: http://collab.di.uniba.it/semotion/

The study of Wrobel [54] reveals how important are emotions for developers productivity. He conducted a survey in order to investigate emotions felt during software development process, how often developers experience specific emotional states during programming and the impact of emotional states on the effectiveness of their work. He found that, in general, negative emotions, especially frustration, disturbs productivity. In some cases, instead, angry has been recognized as a factor that increases productivity. Consistently, developers involved in the survey conducted by Ford and Parnin [16] reported their experience with negative moods experienced in the complex cognitive tasks such as learning a new language, solving tasks with high reasoning complexity, and performing usual programming tasks.

Graziotin et al. [22][23][24] conducted different studies about relationship between emotional state of developers and their productivity. In the first one [24], they investigated how affective states related to a software development task influence the self-assessed productivity of developers, examining the variations of affective states and self-assessed productivity of software developers while developers were programming. They conclude that there is a positive correlation between the affective state dimensions of valence and dominance with the self-assessed productivity of software developers. In a later study [22], they conducted an experiment involving 42 participants in order to investigate the relationship between the affective states, creativity and analytical problem-solving skills of software developers. Subjects have performed one creativity task and one analytical problem solving task. The study shows that happiest software developers are significantly better than analytical problem solvers. In the last work [22], Graziotin et al. have conducted a survey in order to identify the consequences of unhappiness among developers. They found that unhappiness of developers negatively impacts several important software engineering outcomes: productivity and performance are the aspects which suffer most from unhappy developers.

Fritz et al. [18] [50]have monitored developers physiological signals using biometric sensors with the goal to identify the difficulty of code during a comprehension task and to predict code quality online. In particular, they believe that stopping developers before they introduce a bug could be useful to improve software quality. In addition, they suggest to provide recommendations at opportune moments when a developer is stuck and making no progress. This, in fact, could be beneficial for developers productivity. So, authors have conducted an experiment focusing on the relationship between emotions and progress [41]. They found that emotions experienced by developers are correlated with their perceived progress on the change tasks. Furthermore, they build a classifier able to distinguish between positive and negative emotions and between low and high progress.

Fountaine et al. [17] are currently working to predict emotion clarity on progress. Emotional clarity refers to the extent to which people can identify and label their emotions. In their designed experiment, subjects will perform software development tasks while their physiological signals will be recorded using biometric sensors.

5. Problem approach

To detect emotions, different biometric sensors will be used in order to capture physiological signals such as electrodermal activity (EDA), heart rate (HR), electroencephalography (EEG), eye tracker. Noninvasive, low cost devices have been chosen:

BrainLink Mindwave is a headset that monitor electrical brain activity. It has one electrode positioned in FP1 position with reference to 10-20 Internation System of electrodes positioning [30]. The reference electrode, instead, is positioned on the ear. Data recorded from BrainLink are send to Neuroview software, that reports measures related to EEG signal as well as the concentration and meditation levels of the user [6].

Emotiv Insight is a sleek, 5-channel, wireless EEG headset. Designed for everyday use, Insight boasts advanced electronics that are fully optimized to produce clean, robust signals anytime, anywhere. EMOTIV currently measures 6 different emotional and sub-conscious dimensions in real time – Excitement (Arousal), Interest (Valence), Stress (Frustration), Engagement/Boredom, Attention (Focus) and Meditation (Relaxation) [13].

Empatica E4 Wirstbrand is a wearable research device that offers real-time physiological data acquisition and software for in-depth analysis and visualization. The E4 is equipped with sensors designed to gather high-quality data such as EDA sensor for skin-related measures and PPG sensor for heart-related measures [14].

Eye Tribe eye tracking is an eye tracking system that can calculate the location where a person is looking by means of information extracted from person’s face and eyes. The eye gaze coordinates are calculated with respect to a screen the person is looking at, and are represented by a pair of (x, y) coordinates given on the screen coordinate system [15]**.**

Biometric sensors are shown in Figure 1.

BrainLink MindWave (a)

Emotiv Insight (b)

Empatica E4 Wirstrband (c)

EyeTribe eye Tracker (d)

Figure 1. Biometric Sensors to measure physiological signals: EEG (a, b), EDA and PPG (c), eye tracker (d)

Data acquired during experiments will be analyzed, by adopting a machine learning approach to predict emotions from data recorded. Firstly, a pre-processing phase will be applied to remove signal noise introduced from movement artefacts. Later, features that describe signals will be extracted in order to derive information contained into data. Finally, one or more classifiers will be run to build a model for emotion prediction.

6. Expected results

Emotions detection from biometrics can be applied in several different scenarios, especially in e-health and software engineering domain. As result of the project, a notification system of the emotive state and suggestions about the better behavior to adopt based on physiological signals will be developed as a research prototype. This could be integrated, for example, into a smartphone or desktop application. Otherwise, for the case of the software engineering, it can be used as a plugin of an Integrated Development Environment (IDE), such as Eclipse.

In a software company, such a system has three potential stakeholders: the developer, the team and the organization. The developer increases awareness about his own emotions and could use recommendations to became more productive and improving his resilience capability. For example, if the system detects that someone is particularly stressed could support him suggesting to take a break, or do exercises for mental well-being, using smartphone app like “Rize” [49]. At the team level, the team or the Scrum master could understand that an uneven task distribution occurs and they could benefit from information about the emotional state of a member trying to help or support him in solving a task, or simply listening his problems and eventually proposing possible solutions. At the organizational level emotional state information of developers can be used as a feedback about the methodology of development applied. If the company promotes and applies Agile development, detecting that the majority of developers are stressed and frustrated could be an alert that agile principles are not being applied correctly, with the risk of developers’ burnout and high turnover.

In the rehabilitation scenario, real-time identification of patients’ emotions during the medical treatments provides the therapist with a feedback about the treatment and enable adjustment of the medical care accordingly. If the patient reacts with a negative attitude, it will be opportune to relate with him in a different way. In fact, positive and negative emotions might be, respectively, beneficial or detrimental for people’s wellbeing and impact the outcome of the therapy.

In addition, it is important to know if there is an emotional reactions to stimuli also for relatives of patients with impaired consciousness, which cannot communicate. For example, it could be a great success to detect a positive emotional reaction of patients when a relatives speak to them, because it means that the patients are able to feel and reacting to the surrounding social context.

7. Phases of the project

The project is constituted of the following phases: literature review, controlled experiment, case studies and field studies. They are shown in Figure 2.

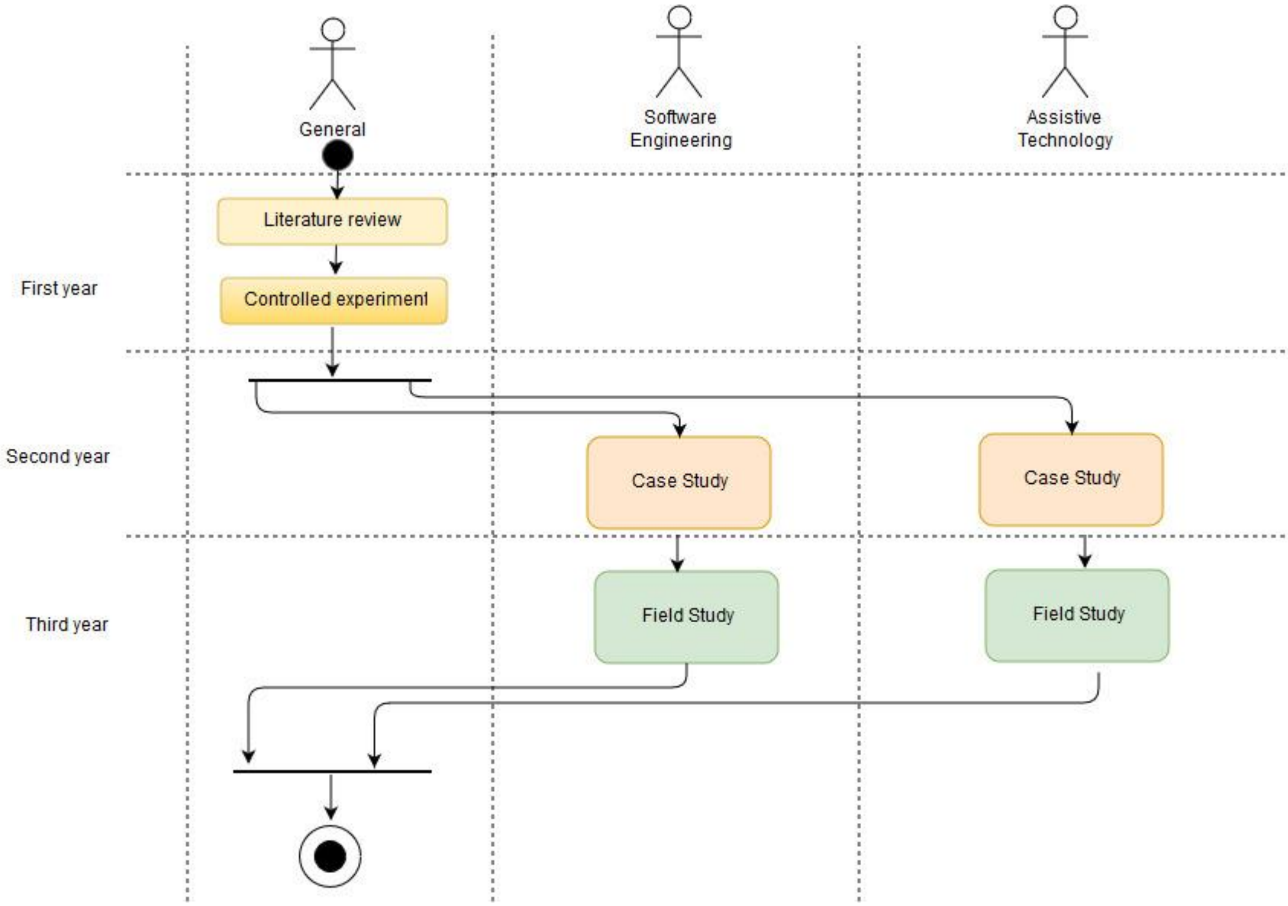

Figure 2. Activity diagram: phases of the project in relation with the years of the PhD.

During the literature review, research about all published papers related to the chosen topic will be conducted through the main digital libraries such as IEEExplore and ACM. In addition, snowballing technique will be applied to find other interesting articles starting from known studies. This initial phase has taken up the first three months of the PhD program. A report describing the current state of the art has been produced, in order to understand which are the domains where emotions detection is relevant, which physiological signals are mainly measured and which biometric sensors are used.

The second phase of the project consists in performing a controlled experiment. For this phase, an initial familiarization with the use of biometric sensors is necessary. The first activity planned is to design the experiment as a replication of [41]. The entire procedure will be defined in detail using a timeline that show every single step and validate with one or two subjects. Successively, there will be the execution of the experiment. Finally, data acquired during execution of experiment will be analysed through pre-processing, feature extraction and classification steps. The duration of this phase will be cover the entire first year of the PhD program. As a result of the controlled experiment and the data analysis, the best set of biometric sensors for emotion detection will be determined.

The third phase will be planned as a case study involving computer science students, using biometric sensors during their project work. The duration of this phase will be cover the entire second year of the PhD program. As a result of the case study, guidelines for usage and data analysis will be defined. A first prototype to get immediate individual feedback will be designed to be integrated within one or more IDEs. In parallel, a repeated case study will be started by involving therapists and families of stroke patients or other relevant pathologies.

The fourth and final phase will be planned as a field study involving professional developers in their own work environment. The duration of this phase will be cover the entire third year of the PhD program. As a result of the field study, guidelines for usage and data analysis will be refined and feedback to improve the prototype will be collected. In parallel, the repeated field study will be continued by collecting data about new patients and then refining the model.

8. Result evaluation

Classical metrics of machine learning evaluation will be calculated to understand how the built classification model performs when applied to a test dataset. They are: precision, recall, F-measure, accuracy.
Precision is defined as the fraction of correct predictions for a certain class, whereas recall is the fraction of instances of a class that were correctly predicted. F-measure is defined as the harmonic mean (or a weighted average) of precision and recall.
Accuracy is is defined as the fraction of instances that are correctly classified.
Statistical test such as McNemar test [37] will be used to compare performance of different classifiers and understand if results obtained from different classifiers or from different set of sensors are statistical different.

9. Possible reference persons external to the department

Possible persons to involve in this project are:

- Maria Teresa Angelillo (ICS Maugeri), as a reference to conduct case and field studies with patients
- Nicola Sanitate (ApuliaSoft), as a reference to conduct case and field studies with software developers
- Davide Fucci (University of Hamburg), as a reference for our ongoing collaboration on design and implementation of controlled experiment related to biometrics in software development
- Andrew Begel (Microsoft Research in Redmond, WA, USA), because his research focuses on biometrics for software development
- Alexander Serebrenik (University of Eindhoven), as a reference for our ongoing collaboration on emotion awareness in software development. Specifically, he is currently working on assessing the emotional labor of software development that involves multimodal emotion detection based on both biometrics and natural language processing of developers' communication traces.

10. References

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