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Mobile platform for affective context-aware systems[☆]

Grzegorz J. Nalepa [a,b,*], Krzysztof Kutt [a], Szymon Bobek [a]

[a] AGH University of Science and Technology, al. Mickiewicza 30, 30-059 Kraków, Poland
[b] Jagiellonian University, ul. Gołębia 24, 31-007 Kraków, Poland

HIGHLIGHTS

- In our work, we focus on detection of affective states, their proper identification and interpretation with use of wearable and mobile devices.
- Furthermore, we formulate a method for personalization of emotion detection.
- This solution offers a non-intrusive measurement thanks to the use of wearable devices, such as wristbands.

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ABSTRACT

In our work, we focus on detection of affective states, their proper identification and interpretation with use of wearable and mobile devices. We propose a data acquisition layer based on wearable devices able to gather physiological data, and we integrate it with mobile context-aware framework. Furthermore, we formulate a method for personalization of emotion detection. This solution offers a non-intrusive measurement thanks to the use of wearable devices, such as wristbands. As means of validation of our concepts we describe a series of experiments that we conducted.

1. Introduction

Cognitive assistants [1] (oftentimes called "smart advisors") for many years have been considered as one of the ultimate computer information technologies to help people in their daily activities. Today, number of such systems exist, and they are well integrated into both online services (e.g. Amazon Alexa) and mobile devices (Apple Siri) [2]. In its technology hype cycle, Gartner[1] still identifies them to be a technology with lots of potential. In order to provide constant and robust decision support, which ranges from general problems to narrow domain specific tasks, they need to process a large volume of data of great variety [3]. Moreover, they need to be able to adapt to the needs and habits of individual users in order to deliver personalized assistance. From technological point of view, they are often developed using the context-aware systems paradigm [4].

Context-aware systems (CAS) are an important class of intelligent systems that gained huge popularity over the last decade [5]. Context in such systems can be described as *any information that can be used to characterize the situation of an entity* [6]. This broad definition allows us to consider a variety of factors as the context: (a) physical, collected using device's sensors, e.g. ambient light luminance and user location, (b) environmental, obtained via software services, e.g. weather and road traffic, (c) organizational, stored in electronic device, e.g. messages and events in a calendar. These values can be treated as a low-level context. Based on them, a high-level context can be generated, by which some *semantics* is introduced, certain *interpretation occurs* and some activities are recognized.

Rapid evolution of personal mobile devices such as smartphones, tablets, smartwatches and other types of wearables, forced researchers and developers to work on efficient methods for modeling and processing contextual information. In our recent research in the area of mobile context-aware systems we identified four challenges that should be met by every context-aware system [7]. These are: intelligibility, efficiency, privacy and robustness. Assuring these requirements is a major challenge for systems that operate in dynamic environment, where contextual information is constantly delivered in a streaming manner. To address the four challenges, in our previous work we proposed a human-readable

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* Corresponding author at:AGH University of Science and Technology, al. Mickiewicza 30, 30-059 Kraków, Poland
E-mail addresses: gjn@agh.edu.pl (G.J. Nalepa), kkutt@agh.edu.pl (K. Kutt), sbobek@agh.edu.pl (S. Bobek).

1 See http://www.gartner.com/technology/research/methodologies/hype-cycle.jsp.

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rule-language that is capable of modeling and processing uncertain knowledge with an efficient rule-engine under the soft real-time constraints. Moreover, knowledge discovery methods from uncertain streaming data were proposed [7].

An important dimension of context can be related to the emotional condition of the user of a cognitive assistant [8]. Affective Computing (AfC) [9] is an interdisciplinary field of study, aimed at computer models and methods for recognizing and expressing emotions. Our main interest is in the detection and interpretation of affective states. Two aspects need to be considered: modes of data collection and ways of interpreting them in correlation with affective states that correspond to emotions. Today, most often harvested and processed information regard speech (prosody), body gestures and poses (e.g. 3D mapping, motion capture), facial expressions (e.g. visual analysis and electromyography) and physiological monitoring (e.g. blood pressure, pulse, galvanic skin response (GSR/EDA)).

In our prior work [10] we assert that a special case of a high-level context may be the emotional state of the user. In such case, *number of problems* to be solved appears. These include: (a) acquisition of physiological data to characterize the emotional condition of a person, in a mostly non intrusive manner, (b) integration of this data into a larger context-processing system, (c) personalization of emotion detection and identification (as there are important individual differences), and also (d) description of a high-level emotional state from low-level contextual data. This paper builds on our previous work and answers some of these challenges.

The *main contribution* of this paper consists in (1) proposal of data acquisition layer based on wearable devices able to gather physiological data, (2) integration of this layer with mobile context-aware framework, (3) formulation of a method for personalization of emotion detection. The rest of the paper is organized as follows: In Section 2 we discuss the main aspects of developing context-aware systems on mobile devices. Section 3 introduces the affective computing paradigm, emphasizing focus of our research. Our motivation for the development of the AfCAI platform is then discussed in Section 4. The development of the platform is described in Section 5. The evaluation of our work at its current stage is provided in Section 6. Related works are discussed in Section 7. Summary and future works are given in Section 8.

2. Context-aware systems

The notion of context has been important in conceptualization of computer systems for many years. Systems that make use of such information are called context-aware systems (CAS). A general observation is that *context is about evolving, structured, and shared information spaces, and that such spaces are designed to serve a particular purpose* [11]. Schilit et al. [12] narrows this definition to be *where you are, who you are with, and what resources are nearby*. A similar definition was given in [13], where context is defined as *individuality, activity, location, time and relations*. One of the most common definition describes context as *any information that can be used to characterize the situation of an entity* [6].

While these definitions differ in details, all of them try to define the context with respect to some entity or individuality — in case of mobile cognitive advisor systems understood as *the user*. This definition perfectly suits the affective computing research area, as the emotional state can be considered as one of the most valuable contextual knowledge about the user. Most of the modern context-aware systems are developed for mobile and IoT platforms. This allows for usage of many independent contexts provided by ambient sensors, motion sensors, biomedical sensors obtained from wearable devices, etc. However, it also imposes several difficulties that the system engineer needs to face. These challenges will be described in following paragraphs.

2.1. Uncertainty handling

Contextual data can be delivered to the mobile context-aware system in several different ways [14], in either of which the system may experience problems caused by the uncertainty of contextual information.

The mobile environment is highly dynamic which requires the uncertainty handling mechanism to adjust itself to rapidly changing conditions. Probabilistic and machine learning approaches cope very well with most common uncertainty types, but they need time to learn and re-learn. What is more, despite the existence of various probabilistic approaches, there is arguably no method that is able to deal with two very different sources of uncertainty: aleatoric uncertainty and epistemic uncertainty [15]. The aleatoric uncertainty is caused by the statistical variability and effects that are inherently random. In the area of mobile context-aware systems this can be reflected as an uncertain sensor readings, which cannot be reduced due to the low quality of sensors or external environmental conditions. Epistemic uncertainty is caused by the lack of knowledge, and can be reduced if additional information is available. Although it is not possible to cope efficiently with aleatoric uncertainty, as much as it is not possible to derive certain conclusion from uncertain data, there is a way to compensate this problem by reducing epistemic uncertainty.

The vital source of information in mobile context-aware systems is the user, who is not only a passive observer of the system but rather its active operator. Therefore, if there is no other automatic source available, the user himself can provide additional information in order to reduce the epistemic uncertainty. However, machine learning methods use a model that is not understandable for the user, and therefore it cannot be modified by him or her. Fuzzy logic approaches can be used to model uncertainty in more understandable form, but they mainly cope with uncertainty caused by the lack of human precision which is not the primary focus in mobile context-aware system. Our previous research proved that one of the best methods for representing contextual information in user-centric systems is a rule-based language equipped with certainty factors and probabilistic interpretation [16]. It provides best trade-off between the efficient uncertainty handling and the ability of the system to be understood by the user. We argue that this solution could be successfully used in affective computing, where the uncertainty has to be resolved by the user himself — especially when it comes to such subjective concepts as emotions.

2.2. System adaptability

Constant *adaptability of context-aware systems* is of the key importance in a user-centric perspective. By adaptability we mean two complementary issues: (1) how the functionality of the system is adapted, i.e. dynamically configured and reconfigured to meet the needs and expectations of a specific user, and (2) how the system should adapt, i.e. tune its operation to the routine habits and needs of a specific user.

This can be further split into long-term adaptability that includes learning user habits and preferences, and short-term adaptability which involves instant reaction to different context conditions. There are approaches that were successfully used in long-term adaptability which involve machine learning, like probabilistic graphical models [17,18]. There are also solutions that allow dynamic reactions to constantly changing context, like complex event processing [19] or rule-based reasoning [5].

In affective computing research area, the adaptability requirement is even more challenging, as the emotional states of the user can change rapidly, much faster than environmental conditions. On the other hand, gradual changes of emotional context are also present in such systems, in a form of mood changes [20].

2.3. Mediation and intelligibility

Mediation techniques were first introduced in 1992 in the domain of databases to cope with integration of knowledge from heterogeneous sources [21]. Over the time, the notion of mediation changed, as more and more standards to describe knowledge were developed (XML, Ontologies, etc.). These standards allow for easier knowledge interchangeability, and hence it was no longer a primary objective of mediation techniques. From a mechanism that allows data fusion, it became a solution that allows modeling dialog between user and the computer system [22]. This allowed to incorporate user into the intelligent system not only as a passive observer, but also as an active operator and supervisor. Dey et al. used mediation in a word predictor system to suggest auto-completion of words and sentences based on the context the user was in [22]. Roy proposed a resource-optimized, quality-assured context mediation framework for sensor networks that uses dynamic Bayesian networks to derive context and deal with context ambiguity or error in a probabilistic manner [23]. Mrissa proposed a mediation approach to solve semantic heterogeneities between composed Web services [24] by exchanging data between them in a context-aware manner.

In affective computing, dialog with the user can be considered as one of the primary means for personalization of the system. Two phases of such personalization can be distinguished:

1. Building affective model: this includes *naming* the emotional state that the user is currently in, but also defining factors that may have impact on that state.
2. Resolving ambiguous context or uncertainty of the model: this includes knowledge mediation between the user and the system in order to improve the model, or to achieve other goals of the system (e.g. recommendations based on the context and the user mood).

In either way, the mediation of knowledge has to be context-aware. This is particularly important in case of affective computing, where user's emotional state may have a tremendous impact on his or her will to participate in a dialog. In our previous research we provided two complementary methods for context-dependent mediation: implicit and explicit mediation. We believe, that these methods could be easily adapted in affective computing to improve adaptability and uncertainty handling.

In the next section we provide a background in affective computing and identify the issues which are of particular interest in our research.

3. Models and methods in affective computing

Affective computing (AfC) is a paradigm originally proposed in 1997 by Rosalind Picard from MIT Media Lab [9]. It uses results of biomedical engineering, psychology, and artificial intelligence. It aims at allowing computer systems to detect, use, and express emotions [25]. It is a constructive and practical approach oriented mainly at improving human-like decision support as well as human–computer interaction. AfC puts interest in design and description of systems that are able to collect, interpret, process (ultimately — simulate) emotional states (affects). Assuming that emotions are both physical and cognitive, they can be studied interdisciplinary by computer science, biomedical engineering and psychology. For AfC there are two crucial elements to be considered: modes of data collection and ways of interpreting them in correlation with affective states corresponding to emotions.

The first is carried out by selection of methods for detecting information about emotions. This means using various sensors which capture data about human physical states and behaviors. Today, most often harvested and processed information are about: speech, body gestures and poses, facial expressions and physiological monitoring. In our research we focus on the last source of signals. We assume a range of wearable physiological sensors capable of monitoring blood pressure, blood volume pulse and galvanic skin response (electrodermal activity).

The second crucial element of affective computing paradigm relies on application of selected algorithms on acquired data to develop models of interpretation for affective states. State of the art methodologies assume the use of the full range of available methods of data classification and interpretation.

Computational models of emotions derive from our interpretation of psychological states and cognitive processes, and are in essence a way to describe the relation between those two phenomena. Affective computing makes its own use of models by applying them to bio-physiological data obtained from sensors in such a way that they can be used in specific software.

Defining "emotion" is a challenge. Modern theories of emotions have their origin in 19th century, as William James theorized about affects in terms of reactions to stimuli. He was precursor to appraisal theory, which is among most popular in the community of computational emotional modeling [26–28]. One of the most popular appraisal theories is OCC (Ortony, Clore & Collins) [29] which categorizes emotion on basis of appraisal of pleasure/displeasure (valence) and intensity (arousal). Valence and arousal are two of several dimensions used to characterize emotional experience [30] (for overview of see [31]). Especially, valence differs states of pleasure and displeasure, and arousal contrasts states of low activation/relaxation and excitation [32,33]. These dimensions are revealed in Autonomic Nervous System (ANS) activity, the part of nervous system responsible for unconscious autonomous functions like respiration and reflex actions. Research indicates that they can be measured by the use of ANS measures, inter alia by the use of Heart Rate (HR) and Skin Conductance/Galvanic Skin Response (GSR) measures (for meta-analysis see [34]). These are quantifiable values that can be measured and processed ascribing different kinds of emotions (i.e. positive self-attribution of intensive value might be interpret as "pride").

Another important set of theories of emotions is less about discrete states and more about relational affect states tracked on a number of continuous dimensions [35]. Dimensional models, similarly to appraisal, map emotion-evoking impulses and states triggered. Popular PAD theory [36] considers Pleasure, Arousal and Dominance dimensions. Different theories of emotion lead to various models which in turn lead to variety of emotion-oriented systems. Good example is EMA [35] — a system implemented on the Soar cognitive architecture which explains dynamic affects through a sequence of triggers. Another system is WASABI [37], believed to be one of most general models of emotion (mainly for simulation).

Furthermore, in the social and behavioral sciences, Scherer [38] attempted to emphasize the importance of definitional issues and their consequences for distinguishing related but fundamentally different affective processes, states and traits, and discussed ways to measure emotion and its components. There were many attempts in recent years to generate a domain-independent model of emotions, and how they affect higher-order cognitive processes. For example, in [39] authors show how psychological theories of emotion shed light on the interaction between emotion and cognition, and thus can inform the design of human-like autonomous agents that must convey these core aspects of human behavior. They proposed a general computational framework of appraisal and coping as a central organizing principle for such systems, and develop a domain-independent model based on this framework, illustrating how it has been applied to the problem of generating behavior for a significant social training application. The model is useful not only for deriving emotional state, but also for informing a number of the behaviors that must be modeled by virtual humans such as facial expressions, dialog management, planning, reacting and social understanding. Moreover, in [40] a generic framework for multimodal emotion recognition was proposed.

In our work, we focus on detection of affective states, their proper identification and interpretation. We do not address the issue of synthesis of emotion. Moreover, for practical reasons, we focus on data about bodily changes of the users that can be captured by sensors of wearable and mobile devices. We initially assume that emotions are results of non-cognitive processes, as James proposed. Furthermore, we assume that it is possible to identify a high-level emotional state from low-level sensory data. More specifically, we are aiming at building on the somatic feedback theory of emotions from Jesse Prinz [41,42], which is based on the James–Lange theory. It is assumed that embodied appraisals manifested by the body and can be detected and measured. In fact Prinz proposes a concept of "core relational themes" that could be possibly identified as patterns in data using data mining. According to Prinz's theory, emotions are build up by two parts: (a) *form* — perception of bodily changes (as in the classical James–Lange theory of emotions [43]) and (b) *content* — relationship between agent and environment. As an example, faster heart rate (*form*) and perception of a loud sudden noise (*content*) build up fear. The answer to the question of how these low-level blocks (*forms* and *contents*) state high-level emotions is among some of the main interests of AfC.

In the next section we outline the specific motivation for our work.

4. Challenges and motivation for the mobile AfC platform

Basically, we are aiming at developing a technology to detect, identify and interpret human emotional states, and then use them in operation of cognitive assistants. We believe that it can be provided based on the integration of context-aware systems and affective computing paradigms. We are planning to identify and characterize affective context data, and provide knowledge-based models to identify and interpret affects based on this data. A working name for our approach and the developed computing platform is *AfCAI: Affective Computing with Context Awareness for Ambient Intelligence*. Such a platform could form an integral part of affective cognitive assistant technology.

We begin this section with the identification of challenges regarding practical operationalization and implementation of AfC models and methods. Then, we move to outlining some opportunities regarding the integration of AfC and CAS paradigms. Finally, we summarize our working assumptions of an affective context-aware model.

4.1. Challenges for building AfC platform

Following our assumptions, we need to measure number of bodily signals to detect and identify emotions. In order to identify these important signals, we begun our work with an in-depth analysis of selected works in experimental psychology and biological psychology. A survey paper [44] provided us with a pool of papers referring to the activity of autonomic nervous system (ANS), which – as with our methodological assumptions – should be viewed as a major component of the emotion response. The paper provides a review of 134 publications that report experimental investigations of emotional effects on peripheral physiological responding in healthy individuals. The results suggests important ANS response specificity in emotion when considering sub types of distinct emotions. Moreover, some terminological assumptions are given. However, from our engineering perspective, the review turned out to be mostly inconclusive and provided little support in designing experiments needed to validate our assumptions.

Some of the conceptual challenges are related to: (1) the use of discrete (e.g. Ekman's faces) or continuous (e.g. Russel's Circumflex with Valence/Arousal) models of emotions, (2) methods of evoking emotions in experimental setup, (3) which bodily signals should be used, how to measure and what to measure, (4) the role of the user feedback (in the lab setup these are questionnaires), in fact people need semantics (names of emotions) — not numbers (e.g. heart rate (HR) values).

There are also some other practical challenges, such as: (5) non intrusive measurement of the signals, (6) the quality of data from mobile/wearable devices, (7) reliable hardware and software setup and data synchronization across several devices, (8) a synthetic way of reporting the measure of emotion.

As far as the last challenge, there are several approaches to do it. Some of them simply assume reporting Valence/Arousal values. We are dedicated to delivering more synthetic methods that would combine data measurements with user reports. Therefore, we are working on certain *affective metrics* that would include both the measurements of bodily responses, as well as report and stimulus evaluation by participants. Some other related works include the so-called Emotional Index [45].

The summary of our working assumptions to address these challenges is as follows.

1. We aim at using continuous models with valence/arousal reports and combine them in the affective context mediation framework with discrete names of emotions provided by users.
2. In the experimental setup, and for calibration, we will focus on visual stimuli in the form of affective pictures selected from the NAPS [32] data base.
3. We focus on the measurement of the heart-related signals including heart rate (HR) and variance (HRV), as well as galvanic skin response (GSR) a.k.a. electrodermal activity (EDA).
4. We will use the feedback from the user in the process of context mediation, for improving emotion detection as well as personalization.
5. The non-intrusive measurement will be provided by wearable devices, such as wristbands.
6. The quality of measurement will be confronted with biomedical hardware.
7. Data synchronization will be provided by custom extensions to a context-aware data collection software.
8. Synthetic reporting will combine both synthetic numerical measures such as Emotional Index, as well as meaningful concepts (names of emotions) established in the process of mediation.

It can be clearly observed, that there is a large variety of models of emotions in the literature. The focus on our work is mostly on non-cognitive models, as the soft-real time measurements of basic bodily signals seem to more feasible to the monitoring of brain activity. While a starting point for us is, as stated previously, the theory of Jesse Prinz, we assume that our architecture can partially address certain heterogeneity of models. First of all, we plan the described next integration of the information about affect as a class of context in context-aware systems. This opens up an opportunity to integrate several different models of emotions. Besides basic monitoring of HR and GSR signals, we are also considering the use of methods for the identification of emotions based on face expressions, and possibly voice monitoring. The outputs from these models could be delivered as possible different kinds of emotional context. The context-aware method could then select between several alternative sources of information. This could address the problem of availability (i.e. not all models would work in all possible conditions), as well as confidence in some models. On the other hand, information fusion of several sources is also considered. While these techniques do not allow to cover a wide range of often incompatible models, they allow for the simultaneous use of several of them.

Next we discuss how these assumptions can be realized thanks to the use of the context-aware systems paradigm.

4.2. Integration of AfC with CAS

The area of affective computing shares some characteristics with the area of mobile context-aware systems that we studied so far. The environment is highly dynamic in both types of systems, as the biomedical information like heart rate reading or blood pressure may change rapidly. Various factors exist that may have impact on the changes of the physiological parameters. These factors may not always be observed, or may be delivered to the system with a degree of uncertainty that needs to be handled appropriately. Finally, the user has to be aware of what the system does with such sensitive data as physiological information. He or she has to understand what is the goal of the system, and should have the ability to adjust the system to follow his or her goals.

We consider a certain hierarchy in interpreting affective context data. In the lowest level, we encounter readings including "physical" context that is delivered by the current mobile phone sensors (temperature, location coordinates), as well as physiological measurements from dedicated biomedical devices (heart rate, skin temperature, galvanic skin response measurement). This data can be considered as objective context. On a higher level, we provide certain conceptualization of this data, which we believe can be provided automatically. Examples include "being at home", or "resting heart rate of given person". Then, on the next level, we would like to provide certain interpretation of that conceptualization, which in the case of the affective data could be "relaxed", "excited", or "anxious". In fact, an ultimate level could include identification of causal relations like explanations and predictions.

Detecting changes in emotional context and explaining them using changes in physiological context could be used to build complex profiles of user emotions. Such profiles could be further used by a computer system to better fit the user preferences, or to react on some alarming changes both in emotional and biomedical contexts. Furthermore, existence of complex profiles of user emotions may lead to creation of general profiles for emotions at all or at specific context which could be used for diversity of cases. Awareness of variation in user emotion in relation to general profile could be then classified as another variable for objective context (weather, location, activity etc.). This general information could be then used for better understanding of user emotions in real situations and better reaction to them. Another case is an introduction of user emotions' awareness into personal artificial assistants, suggestions systems or non-invasive advertisement. It is also valid to discover shortcomings of current generation mobile devices for gathering biomedical context, as well as to be aware and ready to develop tools and methods for future validation and accuracy increase inside framework.

4.3. Context-dependent model of emotions

In affective computing solutions one can identify number of issues related to creating personalized context-dependent model of user emotions. First of all, patterns in biomedical context that may be related to affective state during modeling phase have to be discovered. In the modeling, the basic model that matches user emotions with biomedical signals from wearable devices is built. For this purpose, the publicly available datasets are used, that are known to provoke basic set of emotions. Second of all, correlation between external context and emotional states (biomedical context) need to be identified. The basic model of user emotions built on artificial dataset can be improved with additional data, such as environmental context. However, finding such a complex correlation is a non trivial task. We argue that it can be achieved efficiently with a usage of mediation techniques. Another issue consists in discovering and modeling gradual (mood) and rapid (affect) changes in user emotional state. This challenge is related to the adaptability requirement of mobile context-aware systems. Finally, it is non trivial to properly name the affective state. The basic emotion model which can be built with artificial datasets can be invalid for some users (i.e. some people may react differently to different affective stimuli). Therefore naming the emotional state with a usage of mediation techniques is proposed.

We argue that the achievements in the area of mobile context-aware systems may be extended to address these issues. Fig. 1 shows the workflow of building emotion-aware systems. The workflow is divided into two phases. In the modeling phase, the basic model is built that matches biomedical context to user basic emotional states. In the runtime, the basic model is improved or personalized, with a usage of mediation techniques and machine learning methods, to better fit particular user. The personalization is performed based on the implicit mediation techniques [7,46] and semantic description of emotional states and their possible relations to environmental context.

In the next section we discuss the development of the AfCAI platform based on the concepts discussed in this section.

5. Development of the AfCAI platform

5.1. Architecture proposal

The primary focus of our research was to extend the platform we developed for building mobile context-aware systems [5] with mechanisms for physiological context acquisition, processing and mediation. The architecture of this platform is presented in Fig. 2. It can be defined as an extension of standard Model View Controller software architectural pattern [47] that includes context and adaptability as a part of the model. The *adaptable model* layer of the architecture is responsible for discovery and adaptation to user long-term preferences and habits (profiles), but also should provide mechanisms allowing to react on dynamically changing environmental conditions. The *context-based controller* layer provides mechanisms for context-based mediation between the user and other system components that will allow the system to resolve vagueness and incompleteness of background knowledge data. This layer also provides input for adaptable model layer that supports adaptability of the system by taking into consideration user feedback and other mediators (probabilistic, ontology-based, etc.).

The goal of our research considered in this paper is to extend this basic architecture with two components marked red in Fig. 2:

1. Physiological context provider plugin, responsible for obtaining heart rate, GSR and possibly other data from wearable sensors.
2. Emotion detection and recognition module, which objective is the discovery of correlations between context and user emotional state.

Although these two components do not modify the architecture itself drastically, the development of them is a huge challenge both from technical and scientific perspective.

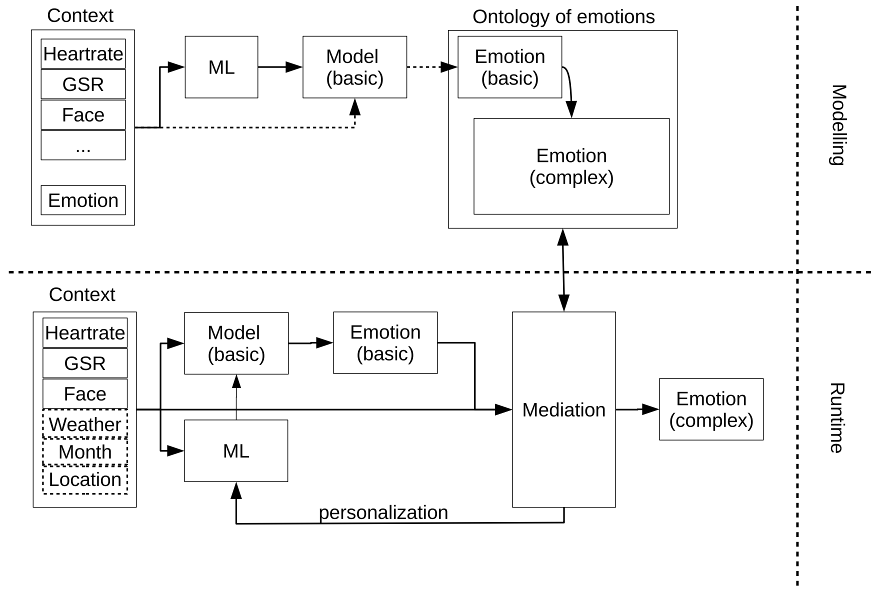


Fig. 1. Two phases of development of emotion aware system.

5.2. Physiological context acquisition layer

One of the main assumptions of our research, outlined in the motivation, was the non-intrusive measurement of physiological signals. We assume an ecological perspective, i.e. the measurement should be possible in a natural environment for the user, and using means which are non intrusive — thus do not have important impact on the measurement. In order to meet this objective, we decided that the physiological context will be obtained from wearable devices. Another important consequence of this decision was that these devices are relatively cheap and accessible. However, they do not necessary provide a high level accuracy and reliability. Yet, they are affordable by most of the people and are non-intrusive comparing to EEG or other professional medical equipment. Our focus was on developing methods that can compensate the low level quality of the hardware, making the affective computing available to broader audience.

This assumption resulted in number of additional practical problems. The first one regards the lack of open standards for communication with wearable devices. Most of the vendors that provide wearable hardware use Bluetooth Low Energy (BLE) technology to communicate with their devices. This communication on the low level is supported by the iBeacon standard. However, this low level communication channel is usually wrapped with vendor specific API, which is not open source, not well documented, and does not allow for direct access to device's sensors. The analysis of the current market allowed us to distinguish about 50 different types of wearable wristbands. To overcome this issue of heterogeneity, we picked only those that allow for direct access to sensors. So far, we used three platforms:

Empatica E4. An advanced sensory wristband based on the technologies previously developed in the Affective Computing division of MIT Media Lab 1. Blood volume pulse and galvanic skin response sensors, as well as infrared thermopile and accelerometer are on board. It has already been used in number of works [48–54].

Microsoft Band 2. Band developed mainly for tracking fitness goals. Equipped with optical heart rate and skin temperature sensors, accelerometer and galvanic skin response (GSR) sensor available through well documented Software Development Kit (SDK).

e-Health Sensor Platform. An open medical monitoring platform supervised by the Cooking Hacks. It is a shield for Arduino/Raspberry Pi and the set of sensors that can be plugged in: pulse, oxygen in blood (SPO2), airflow (breathing), body temperature, electrocardiogram (ECG), glucometer, galvanic skin response (GSR), blood pressure (sphygmomanometer), patient position (accelerometer) and muscle/electromyography sensor (EMG). Thanks to build on Arduino, this solution can be combined with various devices and installations.

We created our own software wrappers that provide a standardized way of obtaining contextual data from these devices. These wrappers were developed as plugins to AWARE platform, which is a mobile instrumentation middleware designed for the purpose of building context-aware applications, collecting data, and studying human behavior [55]. Moreover, we created a dedicated application for Android devices to acquire data from both Empatica E4 and MS Band 2.

Another important practical problem is the lack of standards for storage of physiological context. Most of the wristbands used by us to measure heart rate and GSR provided a way of storing historical records in database. However, this storage was usually controlled by the vendor of the hardware, and did not provide API to query it freely. Moreover, the data that is stored by different hardware providers is often filtered, and preprocessed (e.g. averaged). Lack of documentation of what operations are performed on the data before its storage makes it more difficult to correctly interpret it.

Similarly as in the previous case, we used the AWARE framework and the plugins developed by us as a proxy between the hardware and the MySQL database, where the biomedical context is stored by the framework. This approach allowed us to create a platform for biomedical acquisition that is easily extensible with new hardware, and provides unified storage for different types of wristbands. The mentioned Android application allowed us to get and store data directly on a mobile device, e.g. mobile phone.

5.3. Personalized emotion recognition module

In Fig. 1 a workflow for developing emotion-aware systems was presented, which was divided into two phases. First phase can be viewed as a learning phase, when the basic emotional states are correlated with physiological readings from wearable devices.

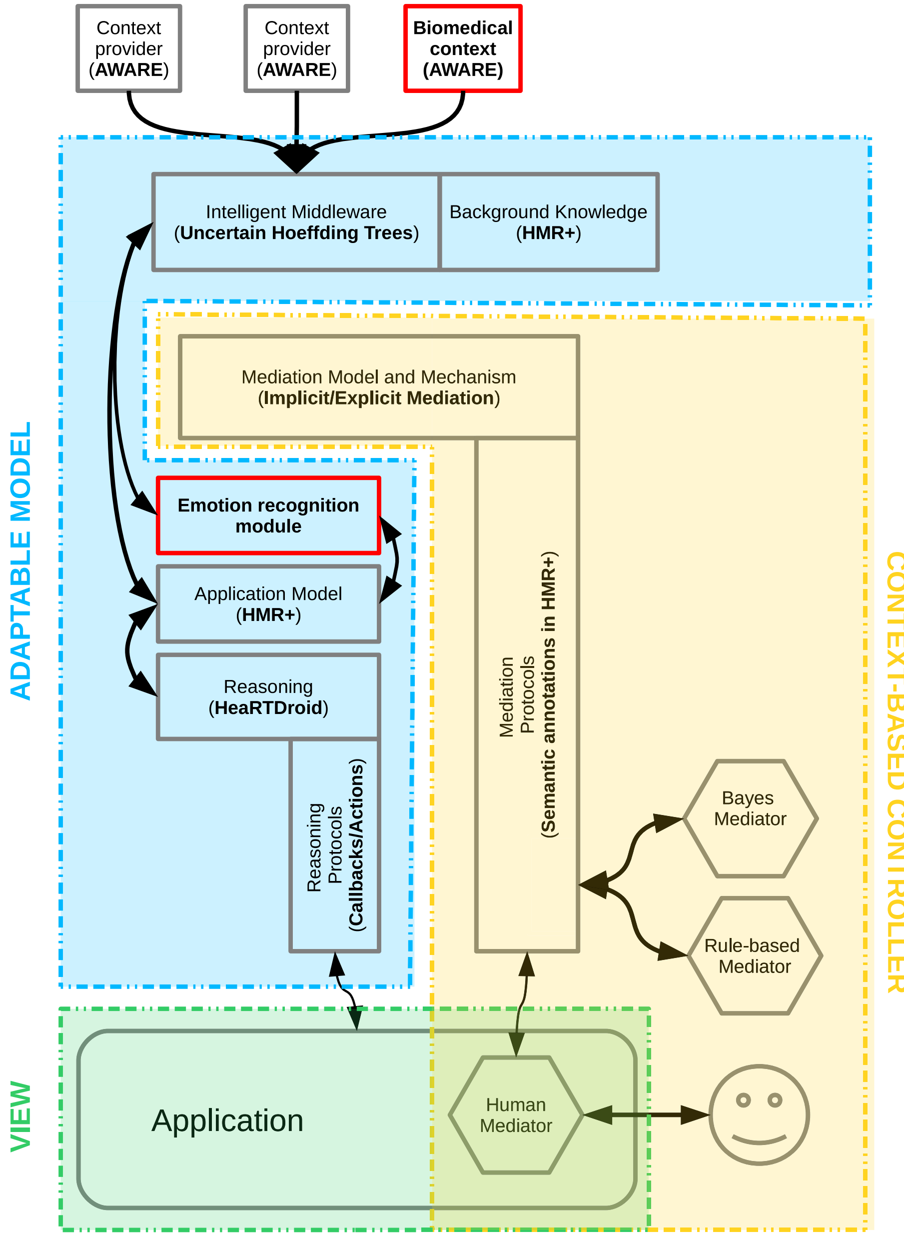


Fig. 2. Architecture for mobile context-aware systems extended with modules for emotion recognition and processing.

Main goal of this phase is to build a model that will be a starting point for the personalization process, and on the other hand will address an issue of cold start of the entire system. In this modeling phase we are planning to build several classifiers based on some freely available affective datasets. So far we are using *DEAP*, a dataset for emotion analysis using EEG, physiological and video.[2] For a similar approach see also [56]. This phase is executed solely in controlled environment, with designed experiments and selected participants.

The second phase is executed in runtime by the emotion recognition component presented in Fig. 2. It begins with the calibration stage, as we assume, that in fact the emotional responses of an individual user differ with respect to specific values of his physiological signals. To address this challenge we provide an initial calibration technique that would allow to tune the acquisition layer. In the calibration phase, we expose the user to a series of visual stimuli provoking emotional response. We use an established database of affective pictures, called the NAPS [32] data base.[3] Based on the previously discussed AfC research on the use of the valence/arousal values in ANS research, the calibration phase was prepared [30]. During it subjects are exposed to affective pictures from NAPS dataset. At the same time current levels of HR and GSR are collected by the wristband. Participants are also asked to evaluate perceived arousal of each of the pictures. The goal of this phase is to combine physiological data with pictures' valence-arousal scores in order to prepare HR and GSR patterns as a function of them.

The experimental procedure was designed in the PsychoPy-Builder. It was then detailed using the PsychoPy 2 (v 1.84.2) environment and executed on notebook, also used for displaying

2 See http://www.eecs.qmul.ac.uk/mmv/datasets/deap.

3 NAPS stands for *Nencki Affective Picture System* (http://lobi.nencki.gov.pl/research/8) and is a set of affective images. The dataset consists of standardized images, as well as normative ratings of valence and arousal for each of them. The database is freely available to the scientific community for noncommercial use by request.

pictures.[4] Physiological data is collected by MS Band 2 and Empatica E4 bands. Bands are paired over Bluetooth with a smartphone, on which the custom application we developed for data acquisition was installed. Data from smartphone and notebook are synchronized using the Lab Stream Layer,[5] a protocol for time-synced data transmission over local network, developed at the Swartz Center for Computational Neuroscience, University of San Diego.

In the second stage of the runtime phase, an adjustment of the basic model (or wraps it with more advanced one) to individual users is provided, as well as emotion identification based on physiological and environmental contexts. Such adjustment is the most critical part of the personalization of the system, and we argue that it can be efficiently achieved with a usage of tools and algorithms developed by us in our previous research, namely uncertain Hoeffding tree mining algorithm [5], uncertain rule-based reasoning [16] and mediation techniques [46].

The uncertain Hoeffding tree mining algorithm allows to discover patterns in uncertain or incomplete data streams by constantly adapting the model, to changing characteristics of data. This allows to capture long term changes in user emotional profile. The algorithm transforms the internal model, which is represented by a decision tree into rule-based representation, which can be immediately executed on the mobile device with HeaRTDroid inference engine. Every ambiguity that appears in the data or in the model can be resolved with mediation techniques, either implicit or explicit [7]. Implicit mediation (also referred to as active mediation or implicit feedback) provides semantic description of the environment and mechanism to utilize this description in order to obtain more detailed information about the current user context. Explicit mediation (also referred to as passive mediation or explicit feedback) aims at improving intelligibility in order to allow direct modification of the knowledge base by the user.

It is worth noting that the first stage is executed solely in controlled environment, and the developed model is then passed to second stage for personalization. Such personalization is supposed to be executed entirely in uncontrolled environment as it corresponds to system runtime. This has serious impact on the system performance in terms of accuracy. In controlled environments participants are selected and usually willing to participate actively in the research. This results in evenly distributed feedback among all investigated emotional states.

In uncontrolled environments the quality of user feedback highly depend on his or her willingness for participation in the research (i.e. emotional state). We assume that some bias towards positive emotions in user feedback can be observed, as people may not be that willingly talk to the system while being angry, anxious, scared, etc.

This issue is planned to be partially solved by the mediation module. This module should be context-aware and do not initiate dialog with the user in situations that are identified as inappropriate. Instead, it should ask about that situations in the future when a context is more suitable for this.

Both mediation mechanisms require semantic description of the domain of interest in a form of ontology. Thus, one of our future works include the design of ontology of emotions.

In the next section we present a series of experiments performed so far to validate our work.

6. Experimental evaluation

AfCAI platform is implemented with the use of wearable devices. This assumes budgetary devices that can be affordable by everyone, but on the other hand these devices should have some minimal level of quality of (affective) data to ensure proper work of the platform. Here four experiments will be described that address the quality of data determination issue (Experiments 6.1–6.3) and physiological affective patterns discovery challenge (Experiment 6.4).

6.1. Experiment 1: secondary school students (July 2016)

First experiment was conducted together with Dr Jan Argasiński (UJ) in order to check the basic setup of mobile devices and identify potential technical issues that should be considered before starting the bigger study. 7 pupils, participants of a holiday camp for secondary school students, were studied using three devices: Empatica E4, Microsoft Band 2 and e-Health Sensor Platform. During the procedure Heart Rate (HR), Galvanic Skin Response (GSR) and Skin Temperature were measured.

The experiment consisted of 4 stages that took place in Virtual Reality (VR) environment created with Oculus Rift device: (a) introduction into VR without interaction with the user, (b) three tasks with architecture tool (changing colors or moving furniture around), (c) "jump scare", (d) another movie without interaction to calm down participants. All was followed by a survey presented at Fig. 3.

About 25 min of recording was obtained by each device for each participant. Preliminary analysis was conducted, leading to many observations that should be considered in the future. Among them the most important were: (a) Synchronization of data between many mobile devices is very important and not trivial issue. They are connected by Bluetooth to smartphone or by cable to computer. Also, some devices do not stream data in real-time but rather pack it into blocks and transmit a block of few observations at once. (b) It is also important to provide an unified way to mark different events in data, e.g. when user makes some action on mobile device or on keyboard connected to the computer as well as when some action was done by the system. (c) Considered devices have to be thoroughly tested and learned by the persons conducting the experiment. Documentation is not always precise and many issues arise during long-time usage, e.g. MS Band 2 by default hibernates after some time. (d) Skin temperature is rather stable and therefore it is not useful in affect differentiation.

6.2. Experiment 2: The Scientist's Night (September and October 2016)

Second experiment was done together with Dr Jan Argasiński to collect data for comparison of bands' signals. 179 participants, guests of the Scientist's Night at Jagiellonian University (September 2016), and 20 Jagiellonian University students (October 2016) took part in a between-subject study, i.e. each participant was studied only with one of three devices (Empatica E4, Microsoft Band 2, e-Health Sensor Platform). Such a plan was adopted due to the nature of the event, to shorten the preparation time to give the possibility of being a participant to many guests. In this experiment only one 5 min long movie[6] was presented in Virtual Reality and followed by the questionnaire (as in previous experiment, see Fig. 3). During the presentation, HR and GSR were measured.

Subjects group consisted of 89 females, 92 males and 18 subjects without defined sex with average age of 19.6 (*SD* =11.1). Their emotional ratings for watched "Lost" movie are presented in Fig. 4. During the event, 166 approximately 5-min long recordings were gathered resulting in nearly 14 h of sensoric data. Unfortunately, only 135 of them were properly paired with questionnaires. Analysis led to generation of average HR waveforms for each device (see

4 PsychoPy (http://psychopy.org) is a standard software framework in Python to support a wide range of neuroscience, psychology and psychophysics experiments.

5 See: https://github.com/sccn/labstreaminglayer.

6 "Lost" movie from Oculus Store, available at: https://www.oculus.com/experiences/rift/1016967501697367/.

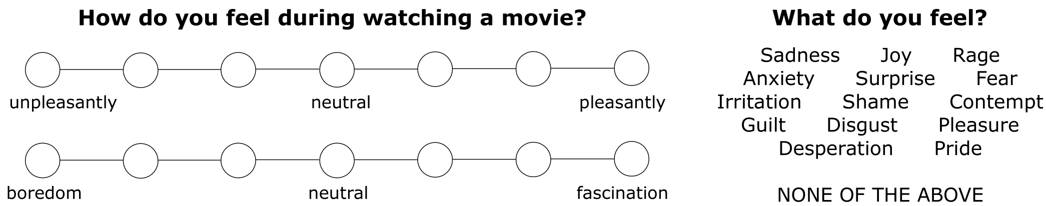


Fig. 3. Survey used in the Experiments 1–2. Form was filled for every stage of experiment. In addition, there was a place for comments below (English adaptation for the paper; during experiments Polish version was used).

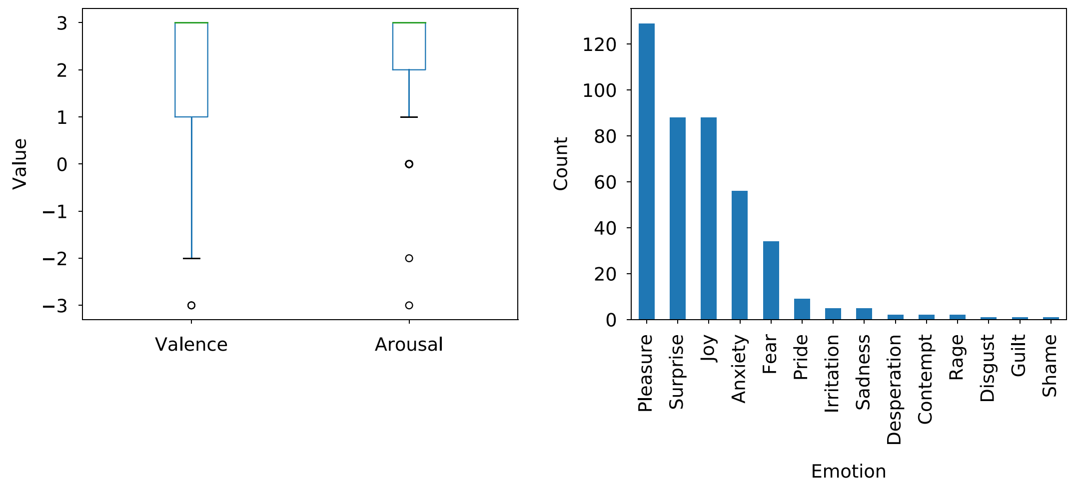


Fig. 4. "Lost" movie emotion ratings.

Fig. 5). It can be easily noticed that they are different, but no conclusions can be made on the basis of this data. First of all, Scientist's Night is a poor environment for conducting experiments. There is a lot of noise and people traffic. Moreover, between-subject plan is a good idea if the devices are trusted. Here, one of the goals was to check their credibility and compare their effectiveness. They are practically impossible to compare by statistical methods in such a plan.

Experience from this study indicates the importance of trusted and well-trained people to help in conducting the experiment. It is also worth noticing that emotional naming (with the use of questionnaire as presented on Fig. 3) is difficult for some people, especially for children who were very involved during the event.

6.3. Experiment 3: comparison with NeXus-10 (Winter 2016/2017)

The goal of the third experiment was to compare budgetary bands signal with medical-class device NeXus-10. It was conducted together with the prof. Maria Trinidad Herrero and prof. Jose Palma from the University of Murcia, Spain. Students of University of Murcia were conducting conducting regular tasks while sitting in front of their computers. No special procedure was conducted.

Finally, 3 sessions with NeXus-10 and MS Band (51 min, 28 min, 66 min; total: 145 min) and 3 sessions with NeXus-10 and Empatica (9 min, 2 min, 41 min; total: 52 min) were recorded. The number of measurements made was small, and the data was often incomplete. For this reason, it is impossible to clearly define the relationship between the parameters recorded by the devices. We conducted an analysis[7] that indicates a high correlation between pulse recordings from MS Band 2 and NeXus-10, and computed from BVP with NeXus-10 and Empatica E4. However, it is necessary to eliminate sudden peaks in computed waveforms. It is also required to mention that Empatica E4's pulse is very smooth and does not reflect quick changes of the parameter being recorded (as it was observed in previous experiment, see Fig. 5c).

6.4. Experiment 4: affective pictures (April 2017)

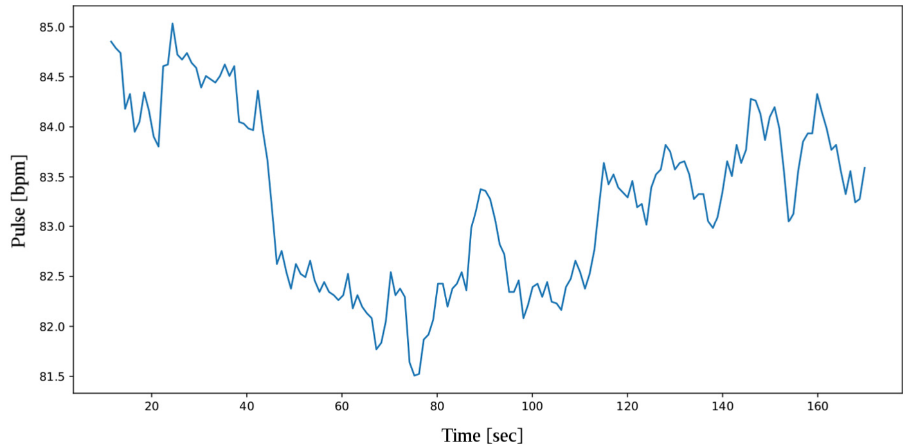
Fourth experiment was conducted[8] in cooperation with Dr Jan Argasiński to gather physiological data linked to affective metric scores. This was the first step to address the challenge of patterns discovery in affective data that matches user emotions with physiological signals [30]. It was also the first practical test of our calibration phase.

Two male and four female participants of the workshop held in the Eurokreator lab, Krakow, Poland took part in about 20 min study. Procedure started with training session where 6 neutral pictures were showed. Task of the subjects was to watch the pictures and to evaluate the emotional arousal after each of them. HR and GSR were acquired before the experiment (as a baseline levels) and during pictures exposition, using Empatica E4 or MS Band 2 bands. During main phase, 10 neutral pictures were mixed with 45 affective pictures (15 pictures evaluated as low valence and high arousal; 15 pictures/high valence and low arousal; 15 pictures/high valence and high arousal). Stimuli and their valence and arousal scores were taken from the Nencki Affective Picture System [32].

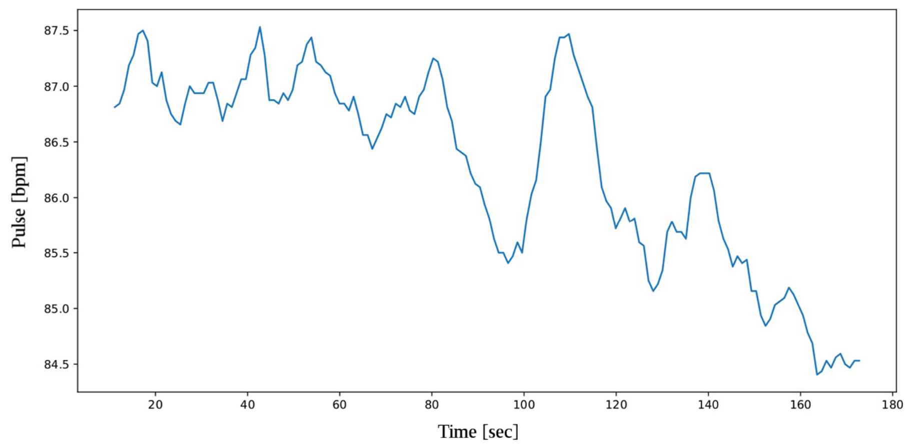
Analysis led to preparation of average HR and GSR waveforms for different emotional stimuli groups (see Fig. 6). Results indicate relationship between HR and arousal: higher HR values are connected with higher arousal scores and lower values are associated with lower arousal scores. Also relationship between GSR and valence can be seen: high valence values are indicated by sudden

[7] It was conducted by Wojciech Binek, Ph.D. student of AGH UST.

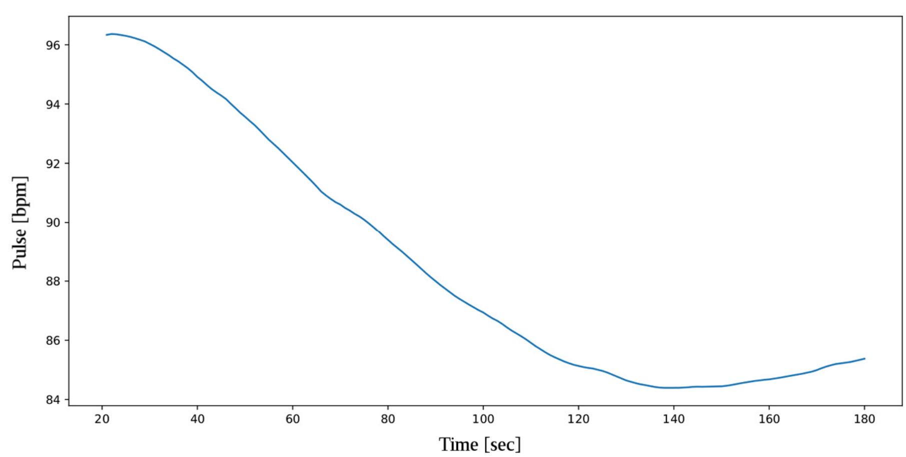
[8] It was partially conducted by Barbara Giżycka, student of Jagiellonian University.



(a) Microsoft Band 2.



(b) Arduino with e-Health Sensor Platform.



(c) Empatica E4.

Fig. 5. Average pulse waveforms for each device used in Scientist's Night.

GSR changes while other valence levels are connected with flat GSR waveforms. These results suggest that budgetary wrist bands are potentially useful for differentiation of emotional states in valence-arousal scheme. It is an important result, as it indicates that development of context-aware platform extended with emotional context is possible.

Further experiments are planned to acquire more data that will lead to more exhaustive analyses. As a result, identification of more accurate HR and GSR patterns is planned.

7. Related works

Our research presented in this paper lays on the edge of two separate areas: affective computing and mobile context-aware systems. As we stated before, we believe that these areas have a lot in common, and both can benefit from combining their achievements. However, related works presented here will be considered separately to make a better point of why our assumptions for combining them is desirable.

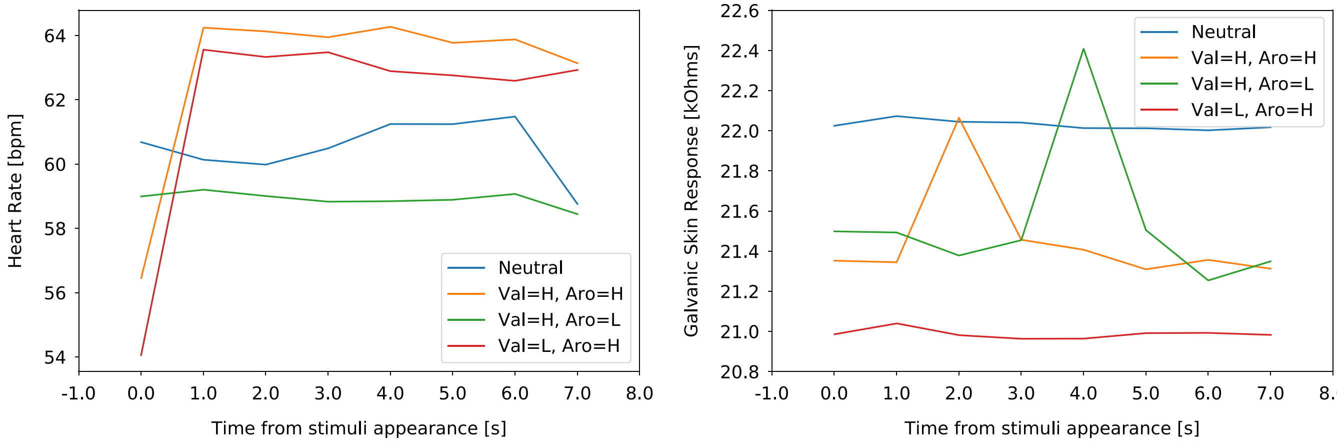


Fig. 6. HR and GSR responses with regard to the group to which the stimulus belonged (`Val` = Valence, `Aro` = Arousal, `H` = High, `L` = Low).

7.1. Mobile context-aware systems

In the area of mobile context-aware systems, the class of systems that may particularly benefit from using affective computing achievements is called *cognitive smart advisors*, or *smart assistants*. These systems can be considered as context-aware recommendation agents that based on information about the environment, as well as user needs and expectations try to optimize his or her daily routines and improve quality of life on many different levels. Numerous such systems have been developed over last three decades. One of the first was Watchdog system, which main task was to execute predefined UNIX commands when some environmental conditions were met [12]. Watchdog used very simple model of context, based on key–value pairs, which does not allow for more complex reasoning. Later ContextToolkit [57] was proposed by Dey, and for the long time it has been the state of the art in the area of modeling context-aware pervasive systems. It used rules as its basic modeling language, which allowed to model more complex systems than in case of Watchdog. However, the rule language was very simple and does not scale well to large models [58]. Along with the growing popularity of ontologies and semantic web, a lot of context-aware systems based on this formalism were proposed. Finally, the popularity of machine learning technologies, especially probabilistic graphical models, caused significant increase of usage of these methods in context-aware systems. In this area, they are often used to model human behavior, activities [59], transportation routines [17], and other areas that operate on large volumes of uncertain and variable data. In [60] the Bayesian model was used to improve the context-dependent recommendations. Han-Saem Park [61] employs Bayesian networks to automatically recognize high-level contexts like activity or emotion of the user, based on mobile device logs.

Hybrid approaches were also proposed that combined strengths of aforementioned techniques, such as CoBrA [62] for building smart meeting rooms, GAIA [63] for active spaces or SOCAM [64] and mobileGaia [65] or MUSIC [66] framework — an open platform for development of self-adaptive mobile applications.

Although most of the methods described in previous paragraphs focus mainly on environmental context or user profiles, there are some that try to incorporate user emotions into the reasoning process. Li and Ji [67] feed a Bayesian Network with face and hand gestures to dynamically model user's affective state to keep the user in a productive state. In [68] attempts to use affective context signals to modulate game scenarios (in Virtual Reality) were presented. Costa et al. use the affective context in iGenda [69] for retirement homes, which primary goal is to utilize the correlation between user daily routines and emotions they cause to discretely improve elderly people lifestyle by proposing activities that will have positive influence on their emotional state. In [8] an exploratory study conducted to understand how audio-visual prompts are understood by people on an emotional level was presented, as a first step towards the more challenging task of designing emotionally aligned prompts for persons with cognitive disabilities such as Alzheimer's disease and related dementias (ADRD).

One of the significant disadvantages of the context-aware systems architectures was that most of them were crafted for the purpose of specific tasks, and hence they are hardly reusable. Furthermore, there was lack of a unified methodology and frameworks for building such systems on mobile devices, which become primary platform for context-aware systems. We addressed these issues in our previous research [5,7], and partially solved them. However, based on our experience, we argue that the area of affective computing is currently facing the same issues that context-aware systems faced at the beginning of the century. Hence, the provision of framework and methodology for developing affective-aware systems should be one of the primary goals for the researchers and developers.

7.2. Affective computing

Affective computing area deals with each stage of emotion processing: detection, usage and expression. Mobile AfC Platform proposed in this paper fits in detection and usage fields where a lot of research is being done.

There are many measurement methods that use medical-class devices (for review see [31,70]). Among them there are: (a) self-reports for measuring subjective experience, (b) autonomic nervous system (ANS) signals (e.g. respiration, reflex actions, EKG, GSR) for measuring peripheral physiology (see also [71]), (c) EEG for measuring central physiology and (d) many behavior metrics, where the most important are vocal characteristics, facial and whole body behavior. Research suggests that Heart Rate (HR) and Skin Conductance/Galvanic Skin Response (GSR) measurements of ANS are useful especially for measuring valence and arousal emotional dimensions (for meta-analysis see [34]).

There are attempts to provide remote methods for gathering various physiological characteristics through remote optical sensors like cameras. Research is primarily focused on heart-related metrics, like pulse or blood oxygen saturation (see [72] for a survey). Studies also cover an affordable for everyone devices and their capabilities in emotion recognition: EEG headsets (e.g. Emotiv EPOC+ helmet) [73–75], 3D scanners (e.g. Microsoft Kinect) [76], web cams [77,78], wrist bands (e.g. Empatica E4, see Section 5), and many others: eye trackers, pressure and posture sensors [79].

An important problem with Affective Computing research is that it mainly focuses on emotions triggered by simple visual stimuli like pictures or short movies. The associated physiological responses and other collected parameters can therefore be a bit biased. However, there are attempts to use also other stimulus: auditory [80], olfactory [81] or more immersive Virtual Reality environment [82]. Interest in multimodal systems is also expressed by organization of the first Audio-Visual+ Emotion recognition Challenge and workshop (AV+EC 2015) aimed at preparation of common benchmark test sets consisting of audio, video and physiological data [83].

Although there is a quite big body of research in emotion recognition, there is still lack in software tools that allow developers (not researchers) to easily integrate such information into applications. Lee et al. [84] propose a framework for mobile applications user interface (UI) development that adjusts the color and movement of the UI elements depending on the emotion defined in two dimensions: valence and arousal. In [79] ABE (Agent-Based Environment) framework is described. It is responsible for gathering data from external sensors (e.g. EEG headsets, eye trackers), integrating them and publishing to the specific application. To enable the reasoning on emotions, Berthelon and Sander [85] propose the Emotion Ontology for Context Awareness (EmOCA).[9] Implicitly based on Jessie Prinz's-like theory, it connects current expression ("John looks angry") with personal traits (context; "John is calm person") to make it possible to infer the real user state ("John is furious"). It uses terms like Valence, Arousal, Emotion, Stimulus.

The overview of relevant related works was helpful in the identification of our future works discussed in the next section.

8. Summary and future work

In the paper we provided background on context-aware systems and their possible integration with affective computing. We introduced a software and hardware platform (AfCAI) that allows for detection, identification and interpretation of human emotional states. It uses physiological measurements provided by wearable devices and a custom context-aware framework. Ultimately, this platform could be an integral part of affective cognitive assistant technology. Our contribution includes specific techniques used in the AfCAI platform, which are data acquisition layer based on wearable devices able to gather physiological data, and a method for personalization of emotion detection. This solution offers non-intrusive measurement thanks to the use of wearable devices, such as wristbands. As means of validation of our concepts we described a series of experiments that we conducted.

There is a number of important directions for the future work on the platform. We are planning extensive works in the area of training and evaluating various classifiers using the DEAP dataset, as well as others. The operation of the classifier has to be integrated with the context-aware reasoning mechanism. Furthermore, as mediation mechanisms require semantic description of the domain of interest, we are planning to develop an ontology of emotions. We are considering the development based on the mentioned Emotion Ontology for Context Awareness (EmOCA) [85]. Moreover, with respect to the scope of the affective context we analyze, in the future we also plan to extend it with the face expression analysis, as well as speech analysis. Finally, we are considering more devices besides the wristbands we now use, as sources of the HR and GSR data. We are aiming at developing a hardware abstraction layer to be able to easily use a range of devices the user might have.

9 Full version is available at: http://ns.inria.fr/emoca/.

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Grzegorz J. Nalepa is an engineer with degrees in computer science-artificial intelligence, and also philosophy. He has been working in the area of intelligent systems and knowledge engineering for over 15 years. He formulated the eXtended Tabular Trees rule representation method, as well as the Semantic Knowledge Engineering approach. He co-authored over 150 research papers in international journals and conferences. He coordinates GEIST—Group for Engineering of Intelligent Systems and Technologies (http://geist.re). For almost 10 years he has been co-chairing the Knowledge and Software Engineering Workshop (KESE) at KI, the German AI conference, and more recently on the Spanish CAEPIA, as well ECAI. He is the President of the Polish Artificial Intelligence Society (PSSI), member of EurAI. He is also a member of IEEE, KES, AI*IA, PTK.