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published in

Proceedings - 2017 IEEE/ACM 2nd International Workshop on Emotion Awareness in Software Engineering, SEmotion 2017
2017

DOI (link to publisher)

[10.1109/SEmotion.2017.8](https://doi.org/10.1109/SEmotion.2017.8)

document version

Peer reviewed version

[Link to publication in VU Research Portal](#)

citation for published version (APA)

Condori Fernandez, O. N., & Suni, F. (2017). Using Emotions to Empower the Self-adaptation Capability of Software Services. In N. Novielli, A. Begel, & W. Maalej (Eds.), *Proceedings - 2017 IEEE/ACM 2nd International Workshop on Emotion Awareness in Software Engineering, SEmotion 2017* (pp. 15-21). [7961886] (Proceedings - 2017 IEEE/ACM 2nd International Workshop on Emotion Awareness in Software Engineering, SEmotion 2017). Institute of Electrical and Electronics Engineers Inc.. <https://doi.org/10.1109/SEmotion.2017.8>

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Using Emotions to Empower the Self-adaptation Capability of Software Services

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Abstract—Traditional self-adaptive systems research has focused on external contextual aspects such as performance, system reaction to environment. In this paper, we introduce the idea of measuring emotions in order to empower the adaptability of software services at runtime. We present two type of monitoring mechanisms and an adaptive adaptation strategy, which were implemented as part of the HAPPYNESS middleware. A preliminary test using data from the Empatica repository was carried out with the purpose of assessing the goodness of the controller (i.e. inference engine), a component of our middleware. The obtained results were consistent with the expected values. Moreover, we test also the connectivity and synchronization between E4-Wristband and an adaptive mobile application that were used by two volunteer users.

Keywords—physiological data, stress, (self) adaptive services, medication adherence, E4-Wristband

I. INTRODUCTION

Nowadays systems in which software interacts with other software, systems, devices, sensors and with people are playing an increasingly dominant role in our lives and daily activities. Moreover, due to the continuous evolution of IT technologies such as wearable sensors, this type of software systems has become more complex but at the same time adaptable. However designing software that can detect the occurrence of changes in the context¹, reason about their effects, and possibly react to them in a self-adaptive manner has become a real challenge for software engineers [1]. In this direction some approaches have been proposed to offer certain capabilities of self-adaptation (e.g. [2], [3], [4]). For instance, Filieri *et al.* approach [4] aims to support self-adaptation by focusing on changes that may occur in the environment in which the application is embedded, or focusing on changes that may affect the satisfaction of technical quality requirements like reliability and performance. In contrast to these works, there is still scarce research on considering user context (e.g. thoughts, feelings, intentions) as input of (self) adaptive systems (e.g. [5]). In this paper, we introduce and develop the idea of exploiting emotional elements of a user's context in order to provide (self)adaptable services and consequently enhance continuously the Quality of User Experience

¹It is defined as any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves

(UX) in context-aware environments. In particular, we measure stress by monitoring physiological data (electrodermal activity, physical activity and skin temperature) of end-users (service consumers). The concept builds on the strength of recent technological advances in emotion measurement tools, non-obtrusive and ubiquitous monitoring technology. We present two type of monitoring mechanisms and an adaptation strategy which is triggered by negative emotions.

The paper is organized as follows, in section II we present some examples of existing wearable devices used to measure emotions by monitoring physiological data. In section III we present the monitoring mechanisms and self-adaptation strategy of the our approach. Section IV illustrates the application of our approach by means of the Health Care Reminder case. This section also presents preliminary results regarding the goodness of our approach. Finally, conclusions and future work are discussed in Section V.

II. EMOTIONS FROM PHYSIOLOGICAL DATA

Physiological data emerged as a prominent source of user information because it provides support for determining different human parameters to understand user behavior (e.g. human emotions). According to Berthelon *et al.* [6], an emotion is produced when exists a stimulus in the central nervous system, then it is expressed on bodily expressions. Now, exist a variety of sensors for monitoring physiological data, such as electrodermal activity (EDA/GSR), blood volume pulse (BVP), heart rate (HR), heart rate variability (HRV), electromyogram (EMG), electrocardiogram (EKG), electroencephalography (EEG), body temperature and physical activity (motion-based activity). Human emotions recognition has largely been investigated in different fields (e.g. Psychology), but the first work about emotion recognition based on physiological data was proposed by Picard [12]. This work found eight emotions that could be categorized in positive and negative characteristics. Later, Picard's team at the MIT Media Lab developed the E4-Wristband², a wearable wireless multi-sensor device for measuring changes on the skin surface communicating the main component of stress. This wearable device was the result of many years of research and evolution of previous versions (e.g. Empatica E3). Several studies have been conducted in the

²<https://www.empatica.com/e4-wristband>

TABLE I
RELATED WORKS COMPARATIVE.

Author	Objective	Device	Physiological data	Recognized emotion
Healey and Picard [7]	Determine driver's relative stress level during real world driving task, through algorithms to detected the onsets and peaks.	FlexComp.	EKG, EMG, EDA and respiration.	Stress.
Tognetti [8]	Enjoyment recognition in a car racing game.	ProComp Infiniti.	BVP, ECG, GSR, respiration and temperature.	Enjoyment.
Muller and Fritz [9]	Classify developers' emotions in the context of software tasks.	Neurosky MindBand EEG, Empatica E3 and Eye Tribe	EDA, EEG, BVP, temperature and HR.	Frustration and happiness.
Lee <i>et al.</i> (Empa talk) [10]	Give the user emotional status while communicating with each other in a video chat.	GSR and BVP sensors, Armband and Arduino.	GSR, BVP, vibrotactile motor and RGB LED.	Enjoyment and engagement.
Leon <i>et al.</i> [11]	Recognizing positive and negative emotional from physiological signals.	Wireless wearable finger clip with built-in sensors.	HR, Skin Resistance, BVP and Gradient of skin resistance	Positive, neutral and negative emotions.

line of emotion recognition in a diversity of situations. For instance, Healey and Picard proposed to detect stress during real-world driving task and they concluded that skin conductance and heart rate are directly related to driver stress [7]. In the area of video games, physiological data has been also investigated in order to understand user experience. For example, Tognetti *et al.* presented a method for enjoyment recognition, (based on BVP, EMG, GSR, respiration and temperature), in a car racing game [8]. Also in software engineering, physiological data is becoming to be consider as important asset to derive emotions when stakeholders (e.g. programmers) perform their corresponding activities. For instance, Muller and Fritz focus their researches on developers' emotions to measure perceived difficulty [13], frustration and happiness [9]. They found that emotional developer experiences are closely correlated with their perceived progress [9]. Table I shows an overview of emotion recognition approaches by monitoring physiological data with different purposes.

III. APPROACH: SELF-ADAPTATION STRATEGY

According to Kazhamiakin *et al.* [14], adaptations can be performed either because monitoring has revealed a problem or because the application identifies possible optimizations or because its execution context has changed.

Fig. 1. Adaptation and monitoring adopted from [14].

Figure 1 shows the relations between the different concepts

for the monitoring and adaptation framework defined within the S-Cube project. These concepts are:

- Monitoring Mechanism refers to any mechanism that can be used to check whether the actual situation corresponds to the expected one. Monitoring mechanisms are used to detect Monitored Events. These events represent the fact that there is critical difference with respect to the expected software state, functionality, and environment.
- Monitored events in turn trigger Adaptation Requirements, which represent the necessity to change the underlying service in order to remove the difference between the actual (or predicted) situation and the expected one.
- In order to satisfy adaptation requirements, it is necessary to define Adaptation Strategies, which define the possible ways to achieve those requirements given the current situation.
- Finally, the adaptation strategies are realized by the Adaptation Mechanisms. These mechanisms include the tools for performing actual adaptation action (Realization Mechanisms), and the tools for making important decisions about the adaptation (Decision Mechanisms). The latter include the mechanisms for selecting adaptation strategies among possible alternatives given the current situations, histories of previous adaptations, user decisions or preferences.

A. Monitoring mechanisms

As shown in Figure 2, we perform monitoring mechanisms at both service and emotion levels in order to enable the context-driven run-time adaptation of a service-based application.

At service level: By monitoring the services, or service-based applications during their actual use or operation. This monitoring activity forms part of the Monitor-Analyze-Plan-Execute (MAPE) loop, where potential service(s) that is(are) causing a not good user experience are monitored.

At emotion level: By monitoring emotions of users who interact with service-based applications. In particular, we are interested in monitoring stress measures, which are derived

from physiological data collected by different sensors. However, in order to identify potential services that could require some adaptation, we need to verify whether negative emotions (i.e. stress) are expressed by a user within the same time interval in which a service is also delivered. We named these emotions as actionable emotions and they are used to trigger the analysis of the SLAs agreements of service(s) that could be causing a negative user experience.

Next, we explain how the adaptation is achieved through decision and realization mechanisms.

B. Adaptation mechanisms

In our approach, we consider actionable emotions as a key driver of the adaptation strategy (i.e. reconfiguration), which is realized by both decision and realization mechanisms. The decision mechanism is implemented as part of the planing activity of the MAPE loop. Therefore the results of the analysis is used by the planning activity in order to build a plan for the i)selection of service configurations, ii) SLAs updating with actual QoS values.

Finally these two type of service adaptation mechanisms can be executed when an end-user negatively experienced using the same service for a frequent number of times; or when a certain number of end-users were not satisfied interacting with the same software service.

Both decision and realization mechanisms are implemented by the Emo-aware controller, which interacts with the interface of the service platform to manage and invoke available services (See Figure 3). It must have a service composition engine and the corresponding planner, so that plans can be specified according to QoS parameters and operational service information can be obtained during their execution.

Next section, we present a service-based mobile application designed for the scenario of medication adherence [15]. This scenario is used to explain about how the HAPPYNESS middleware can be beneficial for delivering adaptable services and enhancing the Quality of User Experience.

IV. THE CASE OF MEDICATION ADHERENCE

Medication *non*-adherence (not accomplish the medical prescription) reduces the quality of life due to disease complication, depression and in the worst cases, death. Therefore, it is crucial to generate new approaches that allow to enhance medication adherence according to user needs. So, different methods have been proposed with this purpose, such as an ingestible sensor system [16] or sensor-augmented pillbox [17]. However, they do not consider user contextual information, which can be used not only for supporting adaptive adaptation strategies but also for monitoring her or his health risk.

In the following sub-section, we describe our Health Care Reminder app and explain how the middleware makes the App self-adaptable.

A. Health Care Reminder App

According to [18], in average elderly people (over 60 year-old), take four or more drugs per day and approximately 20-50% of patients do not take all their prescribed medications. Health Care Reminder is a persuasive mobile application implemented to improve the medication adherence in hypertension patients. Our app focuses on elderly people, therefore the rules of our inference engine are setting with their specific characteristics. The main functionality of Health Care Reminder is to deliver persuasive personalized messages to care receivers. These messages are categorized in four persuasiveness levels based on the six persuasion principles of Cialdini (i.e. Level 1: scarcity, Level 2: Consensus, Level 3: Commitment and Level 4: Authority) [19]. The mobile application architecture and the persuasion strategy were presented in [15].

As we mention in the previous section, the heart of the HAPPYNESS middleware is the emo-aware controller, which is implemented based on the Monitor-Analyzer-Plan-Execution loop. The planing and execution activities are implemented by means of the inference engine (See Figure 4), which in this scenario aims to determine the best configuration of persuasive messages for stimulating the medication adherence. This engine consists of an Artificial Neural Network that calculates hypertension risk from skin temperature, physical activity and EDA signals and an application manager that decides which type of message should be delivered (decision mechanism) and how the message should be delivered (realization mechanism).

The hypertension risk rules were defined according to The American Heart Association³ and The American Institute of Stress⁴. Moreover, the middleware consists also of a Fuzzyfier that transforms EDA values to determine a stress level (See details in [15]). For monitoring the physiological data we use the E4-Wristband, which enable us to derive stress level from the EDA sensor and hypertension risk from EDA, physical activity and temperature. In order to synchronize our App with the E4-Wristband, we used the Empatica API⁵. The API is based on Android and offers developer access to real-time data-streams by Bluetooth connection.

Regarding the services monitoring, only the "message deliver" service was monitored.

B. Analysis and Preliminary results

With the objective of checking the goodness of the inference engine, some initial tests were carried out by means of comparisons between the actual outputs and expected outputs. These tests were conducted in two phases.

1) *Phase I*: In this phase we aim to prove the goodness of the inference engine by using off-line data from Empatica. Empatica⁶ provides recorded data, that was collected with the E4-Wristband device used by a real anonymous user. We

³<http://www.heart.org/>

⁴<http://www.stress.org/>

⁵<http://developer.empatica.com/>

⁶<https://www.empatica.com/demo/connect/allSessions.php>

Fig. 2. The HAPPYNESS middleware

Fig. 3. Overview of middleware embedded in the service platform.

Fig. 4. Inference engine overview.

selected a block of 151815 logs that were collected during ten hours and thirty one minutes. As this block contains logs with mixed physiological data values, it will allow us to test the behavior of the inference engine in different possible situations. The Figures 5(A), (C) and (E) are the native signal of the user that were collected by the E4-Wristband, the Figure 5(B) is the output of our fuzzyfier that converts the EDA values in fuzzy values from zero to one scale, indicating the stress

level (fuzzy sets: low, medium and high). The Figure 5(D) is the hypertension risk that is calculated from EDA, temperature and physical activity. The hypertension risk is an output of the artificial neural network, which it is also used for checking whether care receiver accomplishes the medical prescription. Finally as shown in Figure 5(F), results indicate that 144938 messages were delivered with a level-1 of persuasiveness, 3723 messages with level-2, 1556 messages with level-3, and 1223 messages with level-4. We can observe that level-4 of these last messages was mainly due to the presence of hypertension risk (i.e. values equal to one). Consequently, considering the corresponding stress levels and hypertension risks derived from the corresponding physiological data, all outputs of the inference engine (persuasiveness level) were coherent with the expected values.

2) *Phase II*: In this phase, the tests followed a single-subject design [20], which was carried out with two users working in their own environment (university). The ages of the 2 participants are 20 and 35 years old respectively. The testing was conducted with a double objective: i) to check the connectivity between the E4-Wristband and our mobile application and ii) to analyze if the delivered messages cause any emotional change in the user.

The tests of this phase were performed within two rounds. In the first round, the data collection was carried out when the participants used only the E4-Wristband device. Whereas in the second round, the same participants use the E4-Wristband device and the Health care reminder application. Both rounds took the same duration (20 minutes each round). The first round was conducted mainly for determining the emotional state of each participant before using our mobile application. In the second round, five messages were emitted to each user. The first one was an alert message and it was emitted three minutes before to the intake time. The first persuasive message was issued fifteen seconds after the intake time and

Fig. 5. Results by using offline Empatica data. (A) Electrodermal Activity, (C) Physical Activity and (E) Temperature are inputs to the fuzzyfier and artificial neural network. (B) Stress level is output of the fuzzyfier module. (D) Hypertension Risk that is calculated by the inference engine (artificial neural network). (F) Persuasive level is outcome of the application manager.

the following three persuasive messages was emitted each four minutes. This setting was limited according to users availability. Results shown in 6 correspond only to the second round of the experiment. Figures 6(A) and 6(C) show the EDA values of the User₁ and User₂. The stress level and the moment when was delivered each message by the App are shown in Figures 6(B) and 6(D).

The four delivered persuasive messages for the User₁ and User₂ were of level-1, these outputs were coherent with the respective inputs and there was not any change respect to the

persuasiveness level since the physiological signals remained stable. Moreover, comparing the stress levels collected during the first and second round, we did not observe any emotional change in both users, which could indicate us that the different configurations of the "message deliver" service (i.e. alert message and persuasive message of level-1) were appropriate. However, with a small sample size, these preliminary results need to be interpreted with caution.

Fig. 6. Data collected from User₁ and User₂: Electrodermal Activity collected by E4-wristband (A), (C). Corresponding stress level calculated by the fuzzyfier module and the delivered messages that are output of the application manager (B), (D).

C. Threats to validity

In the following we discussed some threats to validity of our study:

1) *Internal validity*: There is a risk related to the selection of subjects, which was carried out by convenience (i.e. availability of the subjects). However, as we are evaluating the goodness of the inference engine instead of focusing on the effectiveness of the provided service, we think this threat is not very critical.

We acknowledge a threat related to the emotional changes, which could have been observed whether the interaction with the software service was in a longer period.

Another threat is respect to the setting itself, which was mitigated by using their own working environment. However we found out that for one of the two participants (User₁), the delivered messages were indifferent due to the low volume of the audio message. As this threat was detected after running the experiment, for further experiments we plan to adjust manually the volume of our application by considering the auditive capabilities of our participants.

2) *External validation*: Although the study conducted in the second phase involved only two subjects, we think that single-subject design provided us the possibility to evaluate the Health Care Reminder application in their own user's

environment without interrupting their work activities (unobtrusive mode). Moreover, the study facilitated us a greater flexibility for monitoring the user emotions. However, in order to generalize our results about the exploitation of (actionable) emotions as a trigger of adaptation strategies (i.e. service configuration), we need to replicate the experiment in longer periods and with subjects aged over 60 years old.

V. CONCLUSIONS AND FUTURE WORK

In this paper we argue that emotions must be continuously measured in order to have a higher adaptability of software services. To do that, we introduce an adaptation strategy that consider negative emotions (i.e. stress) as an input to our controller (decision and realization mechanisms), which has been preliminary tested in two phases. In a first phase, we used off-line data from the Empatica repository to test the goodness of the inference engine (that implements the planning and execution activities of the MAPE loop). Then in a second phase, we run a second test involving two volunteer users, where we additionally test the connectivity and synchronization between the E4-Wristband device and a mobile application.

Our preliminary results show that our inference engine emits the appropriate persuasiveness level of delivered messages. This means that the different configurations of "message deliver" service were adjusted appropriately according to

the stress level. We also observed that delivered messages apparently did not cause any (negative) effect on the user (for example giving more stress). However, we need to involve more users for confirming these preliminary results. As a future work we plan to conduct an experimental study to assess the adaptability of other services like the scheduler or feedback of the Health Care reminder mobile application. Moreover, we think that evaluating also the effectiveness of persuasive messages could be interesting to assess indirectly the adaptation capability of our controller in the scenario of medication adherence.

ACKNOWLEDGMENT

This work has been partially supported by the Spanish Ministry of Economy, Industry and Competitiveness with the PGE and FEDER Projects: TIN2016-78011-C4-1-R and TIN2013-46238-C4-3-R. We thank also to the two volunteer participants who took part of this study.

REFERENCES

- [1] Nauman A Qureshi, Anna Perini, Neil A Ernst, and John Mylopoulos. Towards a Continuous Requirements Engineering Framework for Self-Adaptive Systems. In *1st International Workshop on requirementsruntime*, pages 9–16, 2010.
- [2] André Almeida, Nelly Bencomo, and Thais Batista. Dynamic Decision-Making based on NFR for Managing Software Variability and Configuration Selection Categories and Subject Descriptors. pages 1376–1382.
- [3] Carlo Ghezzi, Leandro Sales Pinto, Paola Spoletini, and Giordano Tamburrelli. Managing non-functional uncertainty via model-driven adaptivity. *Proceedings - International Conference on Software Engineering*, pages 33–42, 2013.
- [4] Antonio Filieri, Giordano Tamburrelli, and Carlo Ghezzi. Supporting Self-Adaptation via Quantitative Verification and Sensitivity Analysis at Run Time. *IEEE Transactions on Software Engineering*, 42(1):75–99, 2016.
- [5] Shihong Huang and Pedro Miranda. Incorporating Human Intention into Self-Adaptive Systems. In *Proceedings - International Conference on Software Engineering*, 2015.
- [6] Franck Berthelon and Peter Sander. Emotion ontology for context awareness. In *2013 IEEE 4th International Conference on Cognitive Infocommunications (CogInfoCom)*. Institute of Electrical and Electronics Engineers (IEEE), dec 2013.
- [7] J. A. Healey and R. W. Picard. Detecting stress during real-world driving tasks using physiological sensors. *Trans. Intell. Transport. Sys.*, 6(2):156–166, June 2005.
- [8] Simone Tognetti, Maurizio Garbarino, Andrea Tommaso Bonanno, Matteo Matteucci, and Andrea Bonarini. Enjoyment recognition from physiological data in a car racing game. In *Proceedings of the 3rd International Workshop on Affective Interaction in Natural Environments*, AFFINE '10, pages 3–8, New York, NY, USA, 2010. ACM.
- [9] Sebastian C. Müller and Thomas Fritz. Stuck and frustrated or in flow and happy: Sensing developers' emotions and progress. In *Proceedings of the 37th International Conference on Software Engineering - Volume 1*, ICSE '15, pages 688–699, Piscataway, NJ, USA, 2015. IEEE Press.
- [10] Myungho Lee, Kangsoo Kim, Hyunghwan Rho, and Si Jung Kim. Empa talk: A physiological data incorporated human-computer interactions. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '14, pages 1897–1902, New York, NY, USA, 2014. ACM.
- [11] Enrique Leon, Graham Clarke, Victor Callaghan, and Francisco Sepulveda. A user-independent real-time emotion recognition system for software agents in domestic environments. *Eng. Appl. Artif. Intell.*, 20(3):337–345, April 2007.
- [12] Rosalind W. Picard. *Affective Computing*. MIT Press, Cambridge, MA, USA, 1997.
- [13] Sebastian C. Müller. Measuring software developers' perceived difficulty with biometric sensors. In *Proceedings of the 37th International Conference on Software Engineering - Volume 2*, ICSE '15, pages 887–890, Piscataway, NJ, USA, 2015. IEEE Press.
- [14] Raman Kazhamiakin, Salima Benbernou, Luciano Baresi, Pierluigi Plebani, Maike Uhlig, and Olivier Barais. *Adaptation of Service-Based Systems*, pages 117–156. Springer Berlin Heidelberg, Berlin, Heidelberg, 2010.
- [15] Franci Suni Lopez and Nelly Condori-Fernández. Design of an adaptive persuasive mobile application for stimulating the medication adherence. In *Intelligent Technologies for Interactive Entertainment - 8th International Conference, INTETAIN 2016, Utrecht, The Netherlands, June 28-30, 2016, Revised Selected Papers*, pages 99–105, 2016.
- [16] Ioannis Kalpouzos, Kostas Giokas, and Dimitrios Koutsouris. A survey on an ingestible sensor for evaluating medication adherence in elderly people. In *Proceedings of the 8th ACM International Conference on Pervasive Technologies Related to Assistive Environments, PETRA '15*, pages 10:1–10:4, New York, NY, USA, 2015. ACM.
- [17] Matthew L. Lee and Anind K. Dey. Real-time feedback for improving medication taking. In *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems, CHI '14*, pages 2259–2268, New York, NY, USA, 2014. ACM.
- [18] Kim Notenboom, Erna Beers, Diana A. van Riet-Nales, Toine C. G. Egberts, Hubert G. M. Leufkens, Paul A. F. Jansen, and Marcel L. Bouvy. Practical problems with medication use that older people experience: A qualitative study. *Journal of the American Geriatrics Society*, 62(12):2339–2344, dec 2014.
- [19] Robert Cialdini. *Influence : science and practice*. Allyn and Bacon, Boston, MA, 2001.
- [20] J.O. Cooper, T.E. Heron, and W.L. Heward. *Applied Behavior Analysis*. Merrill Publishing Company, 1987.