Stress recognition using connected devices: experimentation feedback

Amira Tlija, Dan Istrate, Said Gattoufi, Az-Eddine Bennani

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TLIJA Amira
BMBI UMR 7338
UTC-Sorbonne universités
Compiègne, France
amira.tlija@utc.fr

ISTRATE Dan
BMBI UMR 7338
UTC-Sorbonne universités
Compiègne, France
dan.istrate@utc.fr

GATTOUFI Said
LR 11ES03 SMART
ISG TUNIS
Tunis, Tunisia
said.gattoufi@isg.rnu.tn

BENNANI Az-eddine
TSH COSTECH
UTC-Sorbonne universités/NEOMA-BS
Compiègne, France
az-eddine.bennani@utc.fr

Abstract*— *The research purpose is to study the impact's use of connected devices on cardiovascular diseases. One of our objective is stress recognition during daily routine life. To achieve that a long term experimentation have been conducted. This longitudinal empirical research study aided by connected devices enabling psycho-physiological monitoring to study the correlation between emotional states including stress levels and prognosis of cardiovascular disease. In this paper, we will present the main participant's feedback concerning the conducted experimentation using wearables sensors. This manuscript explains participant selection. It will not treat data conducted from this experiment or show numerical results. It is a statistical feedback concerning the experimentation protocol. We will clarify the protocol strengths and weaknesses. Our main motivation is to give an opinion to other research and to inspire them if they want to conduct a similar experimentation.

Keywords*—*HRV, wearables sensors, e-health, chronic diseases

I. Introduction

The Internet of Things (IoT) represents a vision of ambient intelligent devices to support smart environments, lifestyles and hyper-connectivity based on the semantic interoperability of network-centric sensor devices as connected objects [1]. It illustrates the inter-connectivity of devices through a wireless network, via Bluetooth or a pre-established protocol. The connected objects are sensors such as the smartwatch, the connected lock, thermostat, smart car, connected scale, etc., that are linked and connected in order to record, communicate and exchange data in real-time. By 2020, it is estimated that the number of the connected objects in the world will almost double to reach 50 billion sensors worldwide, compared to 25 billion objects in 2015 [2]. Montaigne [3] maintained the use of these devices in association with Big Data tools, will contribute to the French Gross Domestic Product (GDP) by an increase of 3.6% in 2020 to 7% by 2025.

Hata [4] maintains that our world is essentially divided into three main areas: the environment and its influence on human beings, the technology that enables the sensing and perception of the environment and physiological and emotional data of the human beings themselves, which in our study in multi-modal HealthCare Monitoring are connected through sensor devices. This is a complex system-of-systems that includes many operators and exploits the IoT architecture. When operating a healthcare system, the patient's environment must be managed ensuring their security and safety. The number of sensors and the need to record data continuously, anonymously, accurately and using a self-synchronised data acquisition method constitute the paradigmatic challenges in this domain. The sensors measure various parameters and provide real-time data streams that need to be processed for data fusion and model building. Hata's health management framework [4] is based on a causality model as is our case study. Sensors measure the psycho-physiological states of the user as well as the relevant states of their living environment and the interaction between them. Emotions and human responses are closely related to hormone balance and the environment (lifestyle, work-style). To analyse emotion, the fact that feelings are personally interpreted must be taken into consideration. Some people cannot or will not identify their feelings. Moreover, even if they do, it is still a personal subjective assessment. For example, a person might state: "I feel stressed" but physiologically it may that the person is just "tired", or "I can feel relaxed" but data shows that "I am stressed", etc. Interactions between different levels, the complexity of data management and decision-making must be taken into consideration.

II. THE PROPOSED WORK AND OTHER RELATED WORKS

There have been no previous studies deploying a similar methodology of longitudinal real-life study of the psycho-physiological correlates of evolution and exacerbation of cardio-vascular conditions. This study was initiated responsive to earlier mainly clinically controlled studies as reported in [5 - 7] which involved data capture in the context of a few specifically detectable activities (such as preparing food, climbing stairs, use the smartphone, etc.). As of 2018 some reported works have been mainly concerned with feature extraction [8]; others have used various approaches for stress detection e.g. a survey approach [9], saliva and cortisol level [10]. Others have used controlled studies to evaluate the impact of a fast food consumption [11] lifestyle in terms of cardio-vascular disease risk and some have involved data capture in an IOT-enabled *controlled* smart home context [12]. However our approach is distinguished in being based on an *ambulant environment* (rather than being clinically controlled), connected-devices-enabled continuous data measurement including contemporaneous self-expression recordings of participant's perceived feelings and mood. The purpose of this project is to determinate relationships between heterogeneous categories of data (physiological and emotional) and to study their impact on chronic conditions, in particular cardiovascular diseases (CVD). The experiments started with data acquisition involving healthy individuals paving the way for addressing the sensor integration, data acquisition, storage and integration issues and evaluating the experimental set-up for the future. Besides explaining the project methodology, this paper will show up the main participant's feedback concerning wearing sensors daily during their routine life.

Experiments have been carried out within INSEAD-Sorbonne Universités. Firstly, the sensor choice was made, secondly, the experimentation questionnaires were tested and validated. Finally, the experimentation and analysis tools were defined. The sensors currently available on the market can support the measurement of three categories of data which provide clues regarding the cardio-vascular function; namely: **i)** the physiological parameters such as activity level, **ii)** arterial pressure, **iii)** stress level. The project proposed to build a system capable of detecting stress amongst other emotions and to analyse the relationships with other variables from the two other categories (physiological and arterial pressure). Moreover, the added value of this study was the monitoring of participants and categorisation of different kinds of emotions, based on their real life but also their physical activity. As the investigations were carried out over a long period, data storage and management had to be ensured.

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III. STRESS RECOGNITION

The heart rate variability is based on the interbeat (RR) interval. We are focusing on analysing heart rate variability based on RR intervall. Many researches have been conducted to show that there is a link between emotion state, physiological and physic activities ([5], [13], [14]).

The HRV analysis (Heart Rate Variability) can be divided into three areas: the long term (within 24h), the short term (about 5 min) and the ultra-short term(less than 5 min). Some research propose the ultra-sort term from 1 min to 4 min [15]. Three metrics can be used for HRV analysis. Between the time domain, the frequency domain and the nonlinear metrics there are about 50 indicators for HRV. Our experience is about monitoring people during daily routine life. The calibration phase duration is about 10 min of meditation (calm respiration in order to calculate the heart rate frequency in a rest condition) and 15 min of stress (stressful games like the stroop color test, mental calculation, etc). The RR interval is being recorded by 1s each time. In the literature, the HRV analysis have been analysed for a short-term duration and 24h measurements. There is a total absent of studies conducted on ultra-short term. Our purpose is to bring out severals indicators the will be relevant to identify each emotional state during ultra-short term experimentation. The software, we aim to use to extract, store and analyze data are as follows:

- Actilife V6.13.3: Analyse actigraph's data
- BP Manager 6.2: Analyse tensiometer data
- SPSS, SQL Server 2012: Statistical tools
- Kubios HRV Standard 3.0.2: Analyse HRV.

IV. WEARABLES SENSORS

During this experimentation, we used three wearables sensors. The tensiometer Rossmax is used to measure the blood pressure variability. Six measures will be done per day: three in the morning and three in the evening. We intend to measure physical activities by wearing actigraph. This sensor should be worn all the day long. In order to measure emotions among stress, we used the heart rate monitor belt polar H7. We ask participants to wear it at least 3 hours per day. For emotion measurement and specifically stress, we carried out a market study for the existing connected objects. We added to that, a state of the art concerning the sensors and emotion. We seek to reconcile our study needs with the existing offers on the market. We have found that there are different tools and methods for emotion quantification[13] specifically the stress, since it is the factor that accentuates the most cardiovascular diseases. Zhu [5] used the survey approach for stress detection, while Boa [6] was interested more by measuring the saliva and cortisol level. Brush [7] evaluate the fast food consumption lifestyle on cardiovascular disease risk.

Fig. 1. Wearables sensors

V. THE EXPERIMENTATION

The experiment is being conducted in collaboration with the INSEAD Sorbonne University. The idea is about equipping participants with wearables sensors in order to measure emotional and physical parameters during their daily life. Before launching the study (See Fig.2), a calibration phase remains essential. We equip participants with ActiGraph GT9X Link and polar H7 and we record the heart rate data during rest condition.

While the first phase is about meditation, the second phase is about boosting participants and stressing them. Speed games and cognitive test are being presented to participants in an interactive way (Fig3.)

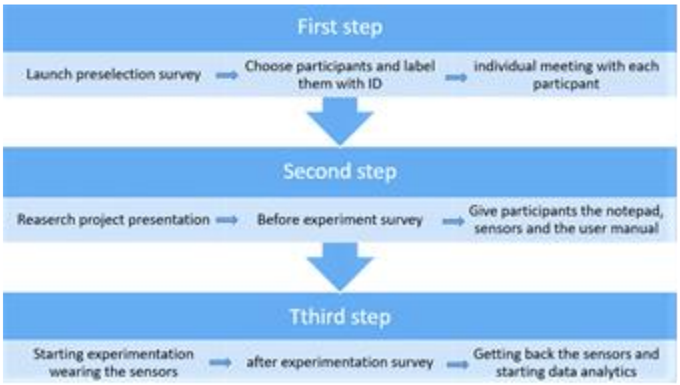

Fig. 2. Study description

During the extended trial as the final phase of the research study a set of three questionnaires will be made accessible online from INSEAD (Qualtrics) to assess the participants' experience of how the study was conducted as follows:

1) Pre-selection survey: with the objective to make an initial selection according to our exclusion criteria.

2) Before trial survey: Once the candidates have been selected and before starting the experiment, they have to answer an online survey whose main objective is to study: personal assessment of the candidate's physical activity, candidate's eating habits, general assessment of the candidate's health (smoking, alcohol, obesity ...).

3) After the trial survey: When they will return the sensors, participant will be asked to first answer a survey whose purpose is to study the candidate's satisfaction with the experience, see if the candidate recommends (or not) the use of wearable sensor devices, find out if the experiment has led to any change occurred in dietary habits/ physical activities, suggestions.(See Fig4)

Fig. 3. Interactives games

VI. PARTICIPANTS FEEDBACK

The experiment's duration was 4 to 5 months during which we worked with 53 people from different socio-professional categories, different levels of study and age category. In this section, we will present some statistical results of the population and participant's feedback after 15 days with wearables sensors.

We aimed to obtain a heterogeneous population conforming to the demographic social criteria of the French population (based on the annual report from INSEE). Recruiting participants conforming to INSEE criteria on 100% was almost hard to achieve. Thus, we favored the heterogeneity of the population based on the criterion "age category". As the graph shows (see Fig.4), almost 40% of our test population are healthy people with no cardiovascular disease who are aged over 40 years.

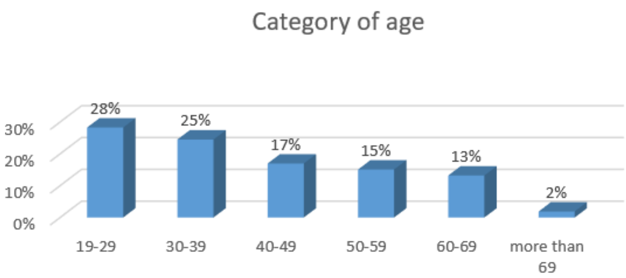

Fig. 4. Category of age

Our final population is composed of ¾ of women and ¼ of men. Obtaining certain variables during sensor initialization allowed us to compare the measurements of the participants. We calculated the body mass index with the following formula: BMI = mass / height^2. The ranking was done as follows:

- If BMI <= 18.5 then underweight
- 18.5 <BMI <= 25 then normal corpulence
- 25 <BMI <= 30 then overweight
- 30 <BMI <= 35 then moderate obesity
- 35 <BMI <= 40 then severe obesity
- 40 <IMC then obesity morbid

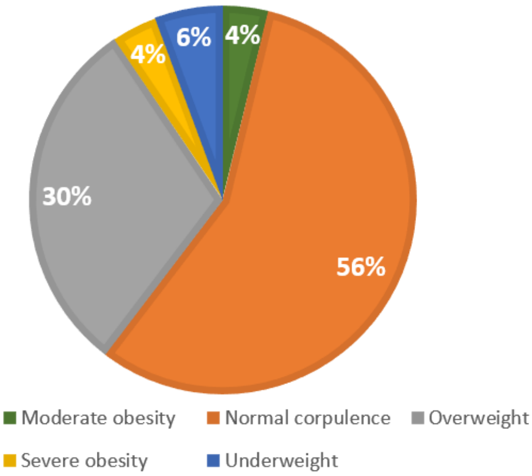

Fig. 5. Obesity level

56% of participants have a normal corpulence and only 4% having severe obesity (see Fig.5)

31% is the wear time validation for less than 40% of participants. This shows that participants were motivated to carry out the experiment. This result is being validated by the analysis of the two main questions in the end of the survey:

Q1: what changes should be done so your assessment for the wearables sensors will be better?

Q2: Do you have any other comments, questions or concerns to share?

TAB.1. What changes should be done so your assessment for the wearables sensors will be better?

The tensiometer's use was not easy	2%
Use more discret wearables sensors	3%
Charging actigraph daily is restrictive	7%
It helped me to do more physical activities	8%
The devices should be more friendly useful	12%
Having an application on the phone to visualise the differents settings	14%
Change actigraph's position	**15%**
Nothing to add	17%
The heart rate belt was uncomfortable	**22%**

TAB.2. Do you have any other comments, questions or concerns to share?

Motivated, but very ambivalent experience	4%
The note book is restrictive to use	8%
Stressful experience	8%
Interested and I would like to have a feedback on my data	8%
Uncomfortable sensors	29%
A rich and unique experience. It helps to better control our daily feelings	42%

As shown in the table above, 22% of participants found that the use of Polar H7 was not comfortable while 15% claimed that it is important to change the actigraph's position.

Some return of candidates can be discussed. Part of the experiment took place in the summer, which may explain the fact that wearing the devices was incomfortbale. The devices chosen had no interface on the phone and this was done in order to keep the data secure.

The device actigraph was small (3cm * 4cm) but with the support the size became more important. For the notepad, we replaced it later with the recorder because we judged that it will make the task easier for the participants.

Despites the fact that participants find these experimentation restrictive but 42% of them said that it was a rich and a unique experience. It helped them to better control their daily feelings.

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REFERENCES

[1] D. Miorandi, S. Sicari, F. De Pellegrini, and I. Chlamtac, "Internet of things: Vision, applications and research challenges," Ad Hoc Networks, vol. 10, no. 7, pp. 1497–1516, 2012.

[2] C. Li, X. Hu, and L. Zhang, "The IoT-based heart disease monitoring system for pervasive healthcare service," Procedia Comput. Sci., vol. 112, pp. 2328–2334, 2017.

[3] I. Montaigne, “Big data et objets connectés Faire de la France un champion,” Rapport, p. +200, 2015.

[4] Y. Hata, S. Kobashi, and H. Nakajima, “Human Health Care System of Systems,” IEEE Syst. J., vol. 3, no. 2, pp. 231–238, 2009.

[5] C. Zhu et W. Sheng, « Multi-sensor fusion for human daily activity recognition in robot-assisted living », in Proceedings of the 4th ACM/IEEE international conference on Human robot interaction, 2009, p. 303–304.

[6] L. Bao et S. S. Intille, « Activity recognition from user-annotated acceleration data », in Pervasive computing, Springer, 2004, p. 1–17.

[7] A. J. Brush, A. K. Karlson, J. Scott, R. Sarin, A. Jacobs, B. Bond, O. Murillo, G. Hunt, M. Sinclair, K. Hammil, et others, « User experiences with activity-based navigation on mobile devices », in Proceedings of the 12th international conference on Human computer interaction with mobile devices and services, 2010, p. 73–82.

[8] D. Huysmans et al., “Unsupervised Learning for Mental Stress Detection - Exploration of Self-organizing Maps,” Proc. 11th Int. Jt. Conf. Biomed. Eng. Syst. Technol., no. January, pp. 26–35, 2018.

[9] M. Buckert, J. Oechssler, and C. Schwieren, “Imitation under stress,” J. Econ. Behav. Organ., vol. 139, pp. 252–266, 2017.

[10] R. Miller, F. Plessow, C. Kirschbaum, and T. Stalder, “Classification criteria for distinguishing cortisol responders from non-responders to psychosocial stress: Evaluation of salivary cortisol pulse detection in panel designs,” Psychosom. Med., vol. 75, no. 9, pp. 832–840, 2013.

[11] M. et al. Poelman, “Relations between the residential fast-food environment and the individual risk of cardiovascular diseases in the Netherlands: a nationwide follow-up study,” Eur. J. Prev. Cardiol., no. April, 2018.

[12] H. Amroun, M. H. H. Temkit, and M. Ammi, “Apprentissage en profondeur des données brutes de l ’ activité humaine In - Depth Learning of Raw Human Activity Data,” pp. 1–7.

[13] H. G. Kim, E. J. Cheon, D. S. Bai, Y. H. Lee, and B. H. Koo, “Stress and heart rate variability: A meta-analysis and review of the literature,” Psychiatry Investig., vol. 15, no. 3, pp. 235–245, 2018.

[14] W. von Rosenberg, T. Chanwimalueang, T. Adjei, U. Jaffer, V. Goverdovsky, and D. P. Mandic, “Resolving ambiguities in the LF/HF ratio: LF-HF scatter plots for the categorization of mental and physical stress from HRV,” Front. Physiol., vol. 8, no. JUN, pp. 1–12, 2017.

[15] Shaffer, F., & Ginsberg, J. P. (2017). An overview of heart rate variability metrics and norms. Frontiers in public health, 5, 258.