An Affective-computing Approach to Provide Enhanced Learning Analytics

Javier Dorado Chaparro[a], Rubén Cantarero Navarro[b], Ana Rubio Ruiz[c], Jesús Fernández-Bermejo Ruiz[d], Xavier Del Toro García[e], María José Santofimia Romero[f], Félix Jesús Villanueva Molina[g] and Juan Carlos López López[h]

School of Computer Science, Computer Architecture and Networking Group, University of Castilla-La Mancha, Paseo de la Universidad Nº4, Ciudad Real, Spain

Keywords: Affective Computing, Learning, Stress, Galvanic Skin Response, Eye-Tracking, Facial Expression, Electroencephalography.

Abstract: Detecting emotions in a learning environment can make the student-learning process more efficient, avoiding stressful situations that might eventually lead to failure, frustation and demotivation. The work presented here describes a perceptive desktop devised to capture the sensations of any person facing learning activities. To this end, we propose a perceptive environment enhanced with capabilities to perform an analysis of electroencephalography, facial expression, eye tracking and particularly a very distinctive indicator of stress as it is the galvanic response of the skin. This work focuses on the galvanic response of the skin, comparing the performance of two devices in the context of the perceptive desktop. One of the devices was very attractive to our environment as it was a mouse that fit very well to our computer-based desktop, equipped with low-cost sensors to detect the galvanic response. The other device is more tedious to place and more expensive but we use it as a reference to know if the mouse is accurate. Four people were exposed to an experiment with the two devices connected, and observing the results it can be concluded that there is no correlation between the captures of both devices. Therefore, we could not select the mouse for our environment even though at first it looks like a very promising device.

1 INTRODUCTION

The use of student-facing learning analytics is gaining attention as it provides information that can help improving the teaching and learning process (Clow, 2012). Learning analytics could be correlated with indicators derived from the student biosignal monitoring. This information will eventually provide a more accurate knowledge of the learning approach that better fits every student individual

The term affective computing is used to refer to technological solutions that capture information about a user's emotions (Picard, 1995). In this sense, the objective of this research is to analyze the feasibility of a perceptive enhanced desktop, with capabilities to assess students emotions. More specifically, the focus will be on identifying those symptoms related to better performance during the learning process.

The proposed desktop is comprised of a set of devices enabling the capturing of different signals. The analysis of these signals will lead to an understanding of the situations that generate discomfort or stress as well as the identification of the environmental factors that impact the most on the student learning process.

In the first part of this article we detail each of the analyses that we are going to carry out in our perceptive desktop, briefly describing the devices that we are going to use to capture each emotion. At the end of this section we will analyze Galvanic Skin Response (GSR) from the point of view of two devices to be as accurate as possible in capturing this parameter, as it

[a] https://orcid.org/0000-0003-4700-5557
[b] https://orcid.org/0000-0003-2893-0392
[c] https://orcid.org/0000-0003-0343-8596
[d] https://orcid.org/0000-0002-4177-4526
[e] https://orcid.org/0000-0002-9996-8008
[f] https://orcid.org/0000-0001-6132-1199
[g] https://orcid.org/0000-0003-0773-5846
[h] https://orcid.org/0000-0002-7372-1568

Chaparro, J., Navarro, R., Ruiz, A., Ruiz, J., García, X., Romero, M., Molina, F. and López, J.
An Affective-computing Approach to Provide Enhanced Learning Analytics.
DOI: 10.5220/0009368401630170
In *Proceedings of the 12th International Conference on Computer Supported Education (CSEDU 2020) - Volume 1*, pages 163-170
ISBN: 978-989-758-417-6

gives us valuable information on stress points. Later, the results of the comparison made between the two devices will be analysed, as well as the placement of each one inside the perceptive desk. Finally, decisions will be made as a result of the results obtained to find the precision in capturing emotions from our desktop and that our future work through this environment to provide guidance.

2 METHODS

Previous studies have used affective computing to capture emotions and thus improve the user experience. In this way, some findings aim to increase the motivation and engagement of users in learning tasks, detecting their emotions within a multimodal environment (García-García et al., 2018). However, as technological solutions are currently in full development, there are many challenges to be faced such as the identification of the state of emotions or the integration of information in multimodal environments (Wu et al., 2016). We plan to extend the affective computing paradigm to promote learning activities adapted to the student individual. To this end, we have designed a perceptive desktop equipped with different devices that, whenever possible will be unobtrusive and non-invasive. First, the user will be prompted to tailored stimuli, provoking them specific emotions. This will be used to train the system on identifying specific emotions. Then, the system will be able to identify those emotions for which it has been trained for and, when possible, will provide the teacher and student the appropriate means to handle the situations.

One of the most significant features to identify stress and cognitive load is the GSR (Sriramprakash et al., 2017) , but in other cases is studied with some other factors such as speech to detect chronic stress (Kurniawan et al., 2013). A desktop environment intended to be aware of stress symptoms has to therefore be equipped with at least a device enabling the GSR measurement. The analysis of the commercial solutions brought about a mouse equipped with the appropriate sensors to measure this feature. There were very attractive features for this device, as it was mainly its low-cost and unobtrusiveness. This device is initially devoted to *gamers* who want to track their constants during a game. For this reason, we decided to evaluate the performance of this mouse with another device specifically devoted to measure GSR. This other device will work as the gold standard, with a more tedious setup but higher precision. The first step in designing the perceptive desktop is to evaluate whether the performance of the mouse is enough to evaluate stress symptoms.

The GSR provides relevant information about our subconscious. Our skin reacts to different stimuli by sweating and we can determine the conductance (or resistance that is the inverse) of the skin at that moment. When the conductance is high, the skin sweats, so we will dictate that the stimulus has provoked a high activation or excitement. In other words, it indicates a high emotional charge, although it is unknown whether the effect is positive (happiness, excitement) or negative (stress, fear, worry). Because of this, although GSR is an ideal measure to track emotional activation, it does not provide information about the emotional valence, i.e. the quality of emotions.

In an effort to capture all the emotional data we have designed a perceptual desktop depicted in Fig. 1. This desktop is comprised of: 1) an electroencephalogram headset to capture the electrical impulses of the brain (Electroencephalogram (EEG)); 2) a depth camera located above the monitor that will be used to detect facial expressions; 3) an eye-tracking camera, located in the lower frame of the monitor that will allow us to determine where our user's attention is focused; 4) the two aforementioned devices to measure GSR and also the Electrocardiogram (ECG).

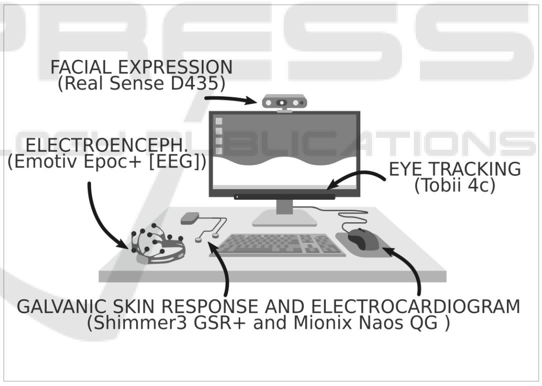

Figure 1: Design of a Perceptive Desktop with Devices to Collect Data from Facial Expression, Eye-Tracking, Electroencephalography, Galvanic Skin Response and Electrocardiogram.

The following subsections describe, in detail, the main characteristics of the device and how they will be used in order to detect emotions and, more specifically, symptoms associated to stress.

2.1 Electroencephalography Analysis

The Brain Computer Interfaces (BCI) is a technology based on obtaining the electrical activity of the brain in order to control an external component. This type of interface allows us to transform our thoughts into real actions, and its field of application is very wide-ranging: from the medical field for the control of robotic prostheses (Mcfarland and Wolpaw, 2010), to the field of leisure and video games (Lécuyer et al., 2008).

There are many devices created by different research groups or manufactured by different companies. However, there are little differences among them as they all have a similar basic function: measure brain activity using sensors, process the signal obtaining its most important characteristics and even interact with the environment as desired by the user.

Despite the many technologies for the acquisition of brain activity, the most effective tool nowadays is the EEG due to its price, flexibility and response time for device control.

The Emotiv EPOC helmet is a non-invasive type of BCI, i.e. its use does not involve physically damaging or penetrating the skin or scalp. A kit including the following items is provided with the product:

- An Emotiv EPOC headset (rechargeable lithium battery).
- A Universal Serial Bus (USB) receiver.
- A hydration pack with 16 sensors.
- A saline solution.
- A USB charger.

The Emotiv EPOC headset has 14 channels that are distributed on the basis of the international 10-20 system. The positioning of the channels is achieved thanks to the plastic branches and two references that ensure the correct position of the electrodes.

Figure 2: Emotiv EPOC Electrode Helmet for the Study of Brain Electrical Activity or Electroencephalography.

The electrodes used by Emotiv EPOC (see Fig. 2) have a small metal disc which is fixed with a conductive paste, enabling very low contact resistance to the signal. In addition to the electrodes, the headset has a gyroscope and two accelerometers that provide information on the movements of the person's head. It also has a wireless transmitter that enables information to be sent to the USB receiver and a battery that powers it. Through these electrodes, treated with a saline solution, we collect the information from each sensor for later analysis and, most importantly, contrast this data with those collected by other sensors on the desktop.

2.2 Facial Expression Analysis

Facial analysis aims to detect the muscle movements that occur in the face, as it is the interface between the world and the emotions. It is therefore the one that allows us to have an image of what we feel, although this can be provoked voluntarily or involuntarily.

There are several ways to retrieve data from facial expression. The Electromiography (EMG) is the most accurate method of capturing data. However, the desktop is equipped with a depth camera able to capture facial movements and to identify and analyze the user's expression in a non-intrusive way. Depth cameras basically work on the basis of two elements, an infrared light projector and an infrared light sensor. In this way, the camera projects beams of infrared light, which the camera sensor will detect, being able to collect the distance to each point and generate a projection of what the camera captures.

Figure 3: RealSense D435 Depth Camera for the Study of Facial Expression Located on the Top of the Perceptive Desktop Monitor.

There are multiple depth cameras available on the market for which different facial recognition algorithms have been implemented. RealSense (see Fig. 3) is one of them, enabling the acquisition of depth images up to 90 fps with a resolution of up to 1920x720. In order to properly capture the data, the camera's location and placement, the room's lighting and the face's visibility have to be taken into account. The information collected from the facial response will indicate the validity of the emotional response and, as with other devices on the desktop, we can compare the results with information obtained by other sensors on the desktop.

2.3 Eye Tracking Analysis

The aim of the eye-tracking analysis is to establish a relationship between the movements of the eye and human cognition. Many fields are involved in eye-tracking to analyze behaviors, and even people's trends. Some of these fields are: neuroscience, advertising, simulation, website testing, learning and education, gaming, medical research... This technology is also used for interacting with a computer system without having to use the traditional keyboard or mouse.

The dilatation of the pupil, the distance to the screen, the direction of our gaze or eye blinking can give us a lot of information about our visual attention, concentration or even the things that we give more importance. The operation of a non-intrusive eye tracker is described by the Pupil Centre Corneal Reflection (PCCR) technique, which basically consists in sending a light to illuminate the eyes, so that the cameras of the device collect those reflections, and through the use of algorithms, the device can identify where you are looking. It is important to have good lighting conditions and a good positioning of the device when collecting data.

Figure 4: Eye Tracking Tobii 4c to Do the Eye-Tracking Study Located in the Lower Frame of the Perceptive Desktop Monitor.

Fig. 4 shows the Tobii 4c eye tracker, which will enable the capture of eye tracking data. These data will be fused with the rest of the data collected from the other devices on the desktop.

2.4 Galvanic Skin Response Analysis

The variation of human sweat can give us enough information about how emotionally activated we are. In order to analyse this, we have to look at the GSR, also known as Electrodermal Activity (EDA) or Skin Conductance Level (SCL). The interesting part of measuring this parameter is that the sweat generated is not consciously produced, but the nervous system activates the sweat glands in the face of an alert. The sympathetic nervous system is in charge of producing this response.

The way to collect the data from SCL is basically to place two electrodes on two fingers, on the sole of the foot or on the sole of the hand. The sensors are usually silver/silver chloride and a constant voltage (low level) is applied to them to measure the voltage difference between the two electrodes. With this non-invasive process you can collect emotional responses that are useful for countless domains, such as psychology, psychotherapy, marketing or even usability studies.

The design used in this research will provide a comparative analysis between two devices that measure the GSR with the aim of being able to have these data available and make a further analysis of the stress peaks. First, we will analyze the data collected with Shimmer3 GSR+ Unit, then we will see in detail how the data is collected with the Mionix mouse. This comparison aims to evaluate different characteristics or parameters of the devices used in order to select one or the other depending on what is needed. Finally, the methodology to collect data from both devices will be discussed in order to compare both systems as well as the assembly of the different sensors in what will be the perceptual desktop designed to capture emotions.

2.4.1 Accuracy Evaluation using Shimmer3 GSR+ Unit

Shimmer is an Irish company that was originally conceived in 2006, although it was not founded until 2008. Since then, it has been regarded as a pioneer in portable sensor technology and solutions.

One of its products is the GSR Unit+, which measures galvanic skin response (GSR) through two reusable electrodes placed on two fingers of one hand. In response to internal and external stimuli, sweat appears on our skin that makes the glands more active, increasing the moisture content in the skin and allowing the electrical current to flow more easily by changing the balance of positive and negative ions in the secreted fluid. In this way, the conductance of the skin increases and the resistance decreases.

To gather the measured data the Consensys program, provided by Shimmer company, is employed, following the next steps:

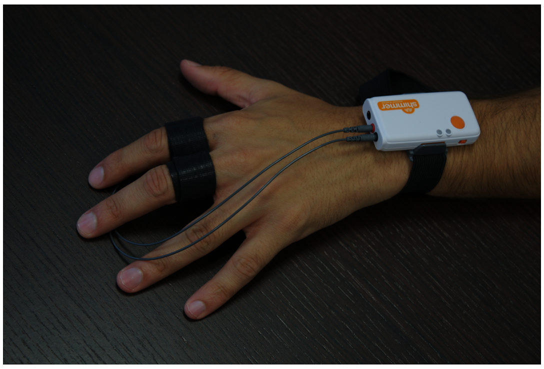

Figure 5: Shimmer3 GSR for the Capture of Galvanic Response Signals from the Skin, Located in the Proximal Phalanx of the Left Hand.

Table 1: Shimmer3 GSR+ Unit Characteristics.

Current draw	60 μA
Measurement range	8kΩ - 4.7MΩ (125μS - 0.2μS) +/- 10%, 22kΩ - 680kΩ (45μS - 1.5μS) +/- 3%
Frequency range	DC-15.9Hz
Input protection	RF/EMI filtering; Current limiting; GSR inputs include defibrillation protection.
Connections	GSR 1 input (red), GSR 2 input (black): Hospital grade 1mm contact proof IEC/EN 60601-1 jacks DIN42-802. Analog/digital auxiliary input: 4 position 3.5 mm connector.
Bias voltage across GSR inputs	0.5V
EEPROM memory	2048 bytes
Weight	30g

1. With the device turned on and plugged into the dock by USB, we start the Consensys program.

2. We select our Shimmer and put the firmware that interests us, in this case we record the LogAndStreamShimmer_v0.11.0 to obtain data by bluetooth and to obtain information of registry in the SD card.

3. The next step is the configuration to measure what we need. For example we can change the data record, the name of our test and device, the sampling frequency and what we want to measure. At the end we have to write the configuration in the device.

4. Place the sensors before collecting the data and then place them where they belong.

5. The last step is to go to live data, connect the bluetooth and look at the data we are getting.

Fig. 5 depicts the appropriate emplacement of the electrodes. In this case, they are placed on the index and middle fingers in the proximal phalanges. After pressing the orange button the device will start capturing data. The last step would be to download and visualize the data, and for it, the Consensys program can be used to download the data in a file Comma-Separated Values (CSV) so we can analyze the GSR.

2.4.2 Accuracy Evaluation using Mionix QG

Mionix is a Swedish company that is known for the development and sale of high performance gaming accessories designed for perfect ergonomics. Their products include keyboards, headphones, and mouse.

The product that we will use in our perceptive environment is the Mouse Mionix Naos QG which has additional sensors that will allow us to monitor heart rate, GSR and the performed activity.

If we look at the sides of the mouse logo, we find on the left the optical sensor for measuring heart rate, and on the right two small metal connectors to get the response of the skin. The operation of the optical sensor is similar to the operation of sensors found in smartwatches, on the other hand, the galvanic skin response sensor measures the conductivity of the skin detecting the level of stress, because the more stress the user has, the more sweat in the palm of the hand and therefore more conductivity.

It can be seen that the features, design and the market to which Mionix is directed are designed for gamers or players to play in a comfortable, accurate way and in this particular model is obtained data on how the player is reacting during the game. However, in the design of our perceptive desktop we thought about this mouse to identify activities in which the user is comfortable or not.

The software that has the mouse is called Mionix Hub, which can be downloaded for free for Windows and MAC to monitor what the sensors read at every moment of the activity. However, there is a Websocket Application Programming Interface (API) for the data to be accessible from any environment and

Figure 6: Mionix Naos QG Mouse for the Capture of Galvanic Response Signals from the Skin Located in the Right Hand.

for any activity for which we need this data(Wulff-Abramsson, 2017).

A Unity program has been developed for data acquisition using this API. This program allows us to collect the information from the GSR in a text file with JavaScript Object Notation (JSON) format.

2.4.3 Experiment Design

The experiment was conducted with 4 volunteers (2 men and 2 women). We have chosen a game that keeps the user stressed during the five or ten minutes of the test, in order to see sudden changes in the galvanic response of the skin, and thus be able to more clearly identify and compare the skin conductance levels in both devices. The test consisted of playing slither.io(Howse, 2016), which is a massive online game involving multiple users which is aimed at growing your worm or snake through the food on the map or other worms or snakes that have been eliminated by hitting their head on the body of another worm or snake. The game, therefore, ends when you hit another worm or snake.

In order to collect data on the galvanic response of the skin, an environment with these components is proposed:

- GSR with Shimmer3: Connected to the computer via Bluetooth for data collection, and placed on the left hand of the user who performs the test. The placement of the device is carried out as explained in the sub-section 2.4.1.
- GSR with Mionix QG: Connected to the computer via USB the user will handle it with the right hand placing the palm of the hand correctly on the electrodes of the mouse.
- Camera for recording user's expressions: The camera is used to get user snapshots and be able to compare their expressions with the data GSR.
- Screen snapshots: The screen is captured to identify the moment in which any alteration may occur in the user.

Once the devices are ready, we run the program to collect data with Shimmer (Consensys), and we also run the program we developed in Unity, taking into account that the sampling frequency of the two devices are the same. For this experiment we have decided to capture 1 sample every second (1Hz), because according to (Geddes and Baker, 1991) the low frequencies are ideal for obtaining the GSR (a range of 0 Hz to 5 Hz is recommended for the collection of this type of measures).

The test takes between 5-10 minutes, and all data and visuals are saved for further analysis. It should be noted that the videos will only be used to make a comparison with the data collected from the GSR devices and therefore will be nonpublished material. Nevertheless, the test participants signed a consent form that makes it clear that their images will not be published at any time, and that they will only be used for comparative testing in this study.

3 RESULTS

3.1 Shimmer3 vs. Mionix Naos QG

When the experiment was over, we could observe the different characteristics of the two devices. First, the range in which the Shimmer3 conductance values are found is between 125μS and 0.2μS as shown in Tab. 1. However, the values we found in the Mionix measurement range are between 0μS and 1μS. Measurement ranges did not match even though we set Shimmer3 to range 3 (Tab. 2) which places values between 1.5μS and 0.2μS.

Table 2: Scale Conductance Range Shimmer3.

Range 0	125μS to 15.9μS
Range 1	15.9μS to 4.5μS
Range 2	4.5μS to 1.5μS
Range 3	1.5μS to 0.2μS
Range 4	Auto-Range

On the other hand, we found that when correlating the data obtained in each device, there is no linear relationship in any of the users exposed to the test. As can be seen in Tab. 3 the results obtained are weak negative (User 1, User 2, User 4) and positive (User 3) relationships.

For a clearer view of the comparison, we can see in Fig. 7 and Fig. 8 that the collected data have no correspondence, and furthermore, in Fig. 8, we can clearly see the moments in which user 1 had higher values of conductance, however in Fig. 7 we are not able to detect the moments in which the user has some kind of excitation.

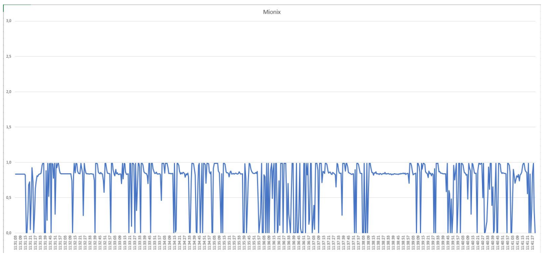

Figure 7: Results Collected on User 1 Using the Mionix Naox QG Mouse.

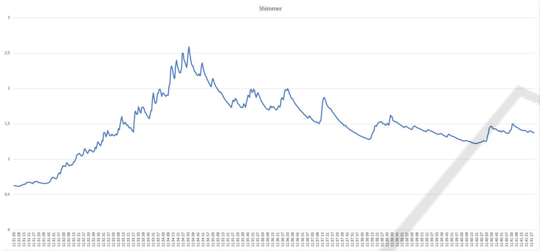

Figure 8: Results Collected on User 1 Using the Shimmer3 GSR Device.

3.2 Perceptive Desktop

The integration of all the devices described for the development of the perceptive desktop can be seen in Fig. 9.

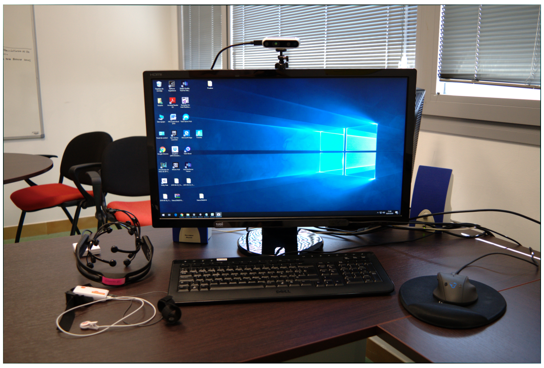

Figure 9: Final Appearance of the Perceptive Desktop with All Devices for Capturing Data.

First, the depth camera is placed on top of the monitor at an ideal angle for collecting facial expressions. Second, the eye tracker is placed in the lower frame of the monitor for eye tracking. On the other hand, when the user is seated on the desktop we will place him/her the EEG headset, the shimmer for the detection of the GSR and ECG and the mouse will be used by the user to carry out the different experiments.

Table 3: Correlation Coefficient.

User 1	-0.026811939
User 2	-0.083538697
User 3	0.066392937
User 4	-0.008630607

4 DISCUSSION

According to the obtained results in the comparison of the two GSR devices, we have observed that the mouse reveals limitations when it comes to perceive changes in GSR. The first fact that we observed to determine the limitations that the mouse had with respect to the other device was that the range of values in which the mouse was moved was a range of values that did not correspond to the values obtained with the Shimmer3 GSR. To determine this first limitation we based on the fact that typical skin resistance values vary from 47 kΩ to 1 MΩ (21μS to 1μS conductivity) (ShimmerSensing, 2015). This fact, made us repeat the tests on the same users to be sure that everything was being carried out correctly, since for example readings may be altered by hand movements during the test or be affected by the position of the palm on the mouse. This leads to a lack of consistency on the observed reading during the testing phase.

It is observed that even in Shimmer, when there is some movement in the electrodes there is fluctuations in data that could not be taken as good. For the assembly of the other devices of the desktop, it is necessary to bear in mind that they are well placed to collect the data, but also the different programs that collect the data have the same sampling frequency for accurate analysis.

In our quest to get an explanation of the values we were getting from the mouse, we sent an email to the Mionix Support Portal to find out if what we were getting was in other units or if the data we were getting was from some conversion. The only answer we received was that the units should be in microsiemens.

Finally, we decided not to take any more samples in the experiment because we saw that the mouse gave us unreliable results, even though we repeated the test over and over again or even collected data from different users.

5 CONCLUSION

The use of learning analytics is gaining attention as it support teachers towards improving the learning process of each student, by shaping the learning process to the approach that better fits the student cognition process. This work presents a desktop environment setup, enhanced with a set of devices capable of perceiving the student emotions, with special focus on identifying the symptoms associated to stress.

This work presents the desktop devices along with the purposes to which each device is intended. Special attention has been devoted to the Galvanic Skin Response (GSR) as it is a reliable sign to detect changes on emotions. Two devices have been evaluated and compared in order to capture GSR data. One is based on mouse-like device which, *a priori*, looks like a very attractive device for being an element present in every computer-based desktop. The other implies a more tedious setup, with electrodes tied to two fingers.

An experiment was conducted to evaluate the accuracy and performance of the mouse-based device (the Mionix) using the Shimmer device as the gold standard. Results have demonstrated that despite being an attractive device for the construction of a perceptive desktop, the obtained measures are not reliable enough for the sought purpose. Further works will consist in combining the data obtained from the different devices and obtain a consistent pattern of work-related stress singnals of individuals.

ACKNOWLEDGEMENTS

This work was supported by European Union's Horizon 2020 programme under grant agreement ID 857159, project SHAPES (Smart and Healthy Ageing through People Engaging in Supportive Systems); Spanish Ministry of Science, Innovation and Universities under Grant PLATINO (TEC2017-86722-C4-4-R); Spanish Ministry of Economy and Competitiveness under Grant CITISIM (TSI-102107-2016-8 ITEA3 Nº 15018); Regional Government of Castilla-La Mancha under Grant SymbIoT (SB-PLY/17/180501/000334); Spanish Ministry of Education, Culture and Sport under Grant FPU Program (ref. FPU 16/06205); and Xavier del Toro García has received financial support from the European Regional Development Fund (Fondo Europeo de Desarrollo Regional, FEDER).

REFERENCES

Clow, D. (2012). The learning analytics cycle: Closing the loop effectively. In *Proceedings of the 2Nd International Conference on Learning Analytics and Knowledge*, LAK '12, pages 134–138, New York, NY, USA. ACM.

García-García, J. M., Penichet, V., Lozano, M., Garrido, J., and Law, E. (2018). Multimodal affective computing to enhance the user experience of educational software applications. *Mobile Information Systems*, 2018:1–10.

Geddes, L. A. and Baker, L. E. (1991). *Principles of Applied Biomedical Instrumentation*. Wiley, London, 3rd edition.

Howse, S. (2016). Slither.io. urlhttp://slither.io/. Accessed 15-07-2019.

Kurniawan, H., Maslov, A., and Pechenizkiy, M. (2013). Stress detection from speech and galvanic skin response signals. In *Proceedings of the 26th IEEE International Symposium on Computer-Based Medical Systems*, pages 209–214.

Lécuyer, A., Lotte, F., Reilly, R. B., Leeb, R., Hirose, M., and Slater, M. (2008). Brain-computer interfaces, virtual reality, and videogames. *Computer*, 41(10):66–72.

Mcfarland, D. J. and Wolpaw, J. R. (2010). Brain–computer interfaces for the operation of robotic and prosthetic devices. *Advances in Computers*, 79:169–187.

Picard, R. W. (1995). Affective computing. Technical report, Massachusetts Institute of Technology.

ShimmerSensing (2015). *GSR+ User Guide Revision 1.8*.

Sriramprakash, S., Prasanna, V., and Murthy, O. (2017). Stress detection in working people. *Procedia Computer Science*, 115:359–366.

Wu, C., Huang, Y., and Hwang, J. (2016). Review of affective computing in education/learning: Trends and challenges. *British Journal of Educational Technology*, 47:1304–1323.

Wulff-Abramsson, A. (2017). Communication framework for the mionix naos qg mouse for online and offline usage. Technical report, Augmented Cognition Lab at Aalborg University Copenhagen.