Correlation Between Types of Obstacles and Stress Level of Blind People in Outdoor Navigation

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***Abstract*—Getting around independently on a daily basis is a challenge for blind people. Indeed, when walking outdoors, blind people must avoid many obstacles to reach their destination safely. The difficulty comes from the great variety of the configuration of the environment, with obstacles that can be static or dynamic, and varying levels of danger. Even if the blind person is already familiar with the environment in which they move, the inherent dynamics of the many objects and actors in the environment are still stressful. This article tackles the question of whether there is a link between physiological stress signals and the obstacles that blind users face when navigating paths and routes in daily life. We designed and proposed two prototypes using biological sensors connected to a cane for blind people to collect data in several scenarios. Methods and analysis that were applied on the collected data in order to detect stress will be discussed along with all the results achieved. This work shows that stress can be identified and detected when a blind person is navigating a path, and even that the stress factors causing this stress can be related to obstacles along the path.**

***Index Terms*—stress analysis, blind people, data collection**

I. Introduction

Stress can be defined as a state of physical or mental tension resulting in different feelings or emotions. It comes from any situation that makes a human being frustrated, nervous and angry. Every human being is subject to stressful situations, and obviously the most stressful situation or event in the daily lives of blind people is autonomous navigation. Even if the navigation path is known, the changing dynamics of the environment related to different parameters such as the time of day, the nature of the obstacles that may be encountered, etc., turn this into a challenge. Stress can be directly related to many physiological signals, indeed when stressed, the human body reacts to stress with a response called General Adaptation Syndrome (GAS). GAS is divided into three stages. The first stage is called alarm, fight or flight, it is the stage on which this study has focused and is the body's immediate response to stress where heart rate, skin conductance and muscle activity increase [1], [2]. In a previous article [3], the authors focused on describing stress and its impact on human life, especially for blind people. Furthermore, this work also described how the human body responds to stress and how stress is related to certain biological signals. A prototype of cane was presented, which measures some biosignals, for blind people navigating an experimental path, as well as preliminary studies on the data collected using this smart white cane.

This paper extends and deepens the works of the authors' previous research. First, a second prototype has been designed to acquire more accurate biosignal measures thanks to a BITalino kit [4]. Second, further experiments were conducted using a slightly modified protocol: the experimental path was divided into three sectors and users, blindfolded, indicated their stress level on a scale of 1 to 10 at the beginning, middle and end of each sector. Third, this paper focuses on identifying stress and specifically the correlation, if any, between stress and obstacles encountered in the path of blind users during navigation, in order to contribute to blind navigation by making this task less stressful and easier in the future.

The remainder of this paper is organized as follows. Section II presents a summary of related studies. The next section describes how physical data are collected, more particularly the two prototypes of smart canes that were designed and the experiment area as well as the kind of obstacles. Section IV presents the experimental protocol and the obtained dataset. The data are analyzed in Section V while Section VI discusses the results. Finally, some conclusions are drawn and future work is indicated.

II. Related Work

This section presents some related work. All of the studies below tackle stress detection by monitoring biological signals in people.

Kalimeri *et al.* [5] developed an approach to detect stress for blind persons during indoor navigation based on the signals of the electroencephalogram (EEG) by the EmotivEpoc+ equipment, the signals of the EDA, and blood volume pulse (BVP) by the Empatica E4 equipment. The indoor navigation route experiment included five distinct environments representative of a variety of indoor mobility challenges. Participants had to enter through automated doors, use an elevator, move across a busy open space, walk down a large spiral staircase, and walk through other obstacles. The route was approximately 200 meters in length and took on average 5 minutes to walk (a range of 4–8 minutes). Massot *et al.* [6] have presented a case study where a wearable device called EmoSense is used on blind pedestrians to monitor the Autonomic Nervous System

(ANS) in an ambulatory, non-laboratory settings experiment. EmoSense is a small wrist device connected to several sensors, affording the measurement of physiological signals from the sympathetic and parasympathetic systems, such as Skin Resistance Responses (SRRs), Skin Temperature (ST) and Heart Rate (HR). The recording and the analysis of these signals were carried out to allow an objective evaluation of the stress for blind people moving in the city, and then to approach the phenomenon in a more precise way (by localization). The aim is to verify the hypothesis put forward by psychologists stating that the urban environment has an effect on the stress and vigilance of blind people. Moreno et al. [7] presented a study to investigate the autonomic nervous system modulation on the heart of blind people but also on sujects benefiting from a normal vision and submitted to a low vision situation. Normal vision subjects and blind patients were submitted to Heart Rate Variability (HRV) analysis during resting, intervention and recovery periods. Intervention consisted of handling objects, taking short walks, and performing activities with pedagogic games while wearing sleeping masks.

Zubair et al. [8] designed a cost-effective, low-power, IoT-based smart bracelet for healthcare that detects mental stress based on skin conductance. This wristband can continuously monitor the user's mental stress and wirelessly transmit stress-related data to the user's smartphone. Kalhoro et al. [9] presented a data collection protocol for the ambulatory recording of physiological parameters for stress measurement purposes. They presented a wearable sensor system for the ambulatory recording of ECG, EMG, respiration and skin conductance. The system also recorded various context parameters: acceleration, temperature and relative humidity. They showed that the sensor system is capable of long-term, noninvasive, nonobtrusive, wireless physiological monitoring and also presented some preliminary results of a stress estimation method. In 2016 the Amulet [10] team conducted two studies to monitor stress. The team collected data from subjects where all of the participants wore devices respectively called the Amulet and the Zephyr. The Zephyr (a chest device) was transmitting heart rate data to the Amulet (a wristworn device). After each study the researchers developed an algorithm for stress detection.

Many researchers have also worked on the design of intelligent canes. Hence Huang *et al.* [11] used a smart cane that contains force sensors and a CCD camera for a falling detection system. This work investigates whether the distance between the center of the legs and the cane can be used to classify the subject's activity. In the context of blind people, the following devices can be noticed. EyeCane [12] aims to guide blind people using vibrations and sound effects where the intensity of sound and vibration depend on the proximity of the obstacles detected. UltraCane [13] has provided an alternative, namely an assistive technology that safely avoids obstacles and navigates around them. It also provides valuable protection at head and chest levels. UltraCane detects street furniture and other obstacles within 2.4 meters. TomPouce [14] is an electronic box that can be fixed on an original white cane to automatically transform it into a smart cane. It is based on infrared and laser beams pointed to the front. The objective is to detect moving and static obstacles while indicating distances.

In addition to stress detection, the aim of this research work is to identify whether there is a relationship between the obstacles encountered by blind pedestrians and the amount of stress that can be detected in order to cope with this stress by anticipating it.

III. Physiological Data Collection

After publishing the previous article [3], a prototype was built and evaluated. Over time, the prototype was expanded and further experiments were conducted using the updated version. To differentiate both versions, the first version can be referred to as the first prototype and the current version as the second prototype. The upgrade was the result of further research since the publication of the previous paper and aimed at obtaining a more accurate measurement of biosignals.

A. Prototypes Description

The first prototype is an assembly of a cane, heartbeat, skin conductance, muscle activity sensors, and an Arduino controller board. The cane is also equipped with an ultrasonic sensor that allows a blindfolded user to scan his environment and measure the distance to obstacles. The ultrasonic sensor and physiological sensors are all connected to an Arduino board. The board transmits all the sensors measures each second via a Bluetooth module thanks to a mobile application. This mobile application stores all the data measured in a Firebase database. Fig. 1 gives an overview of the first prototype.

As mentioned earlier the second prototype is the result of some modifications that were made on the first one to achieve more accurate data collection. Indeed, the physiological sensors of the first prototype were replaced by BITalino [15], [16] Plugged Kit and the android application was updated to communicate successfully via the Bluetooth module integrated within the BITalino board. The BITalino kit is a versatile solution for designing different signal acquisition experiments. It comes with ECG (electrocardiogram), EMG (electromyography), EEG (electroencephalogram) and EDA (electrodermal activity) sensors. The EMG and EDA sensors were used, while the ECG sensor was replaced by the Xiaomi band 5 for heartbeat acquisition.

B. Obstacles Observation and Classification

Fig. 2 shows the experiment area where the walking path is highlighted in blue. As can be seen it is a road that starts from point A and reaches point B which represents the public municipality building in Jezzine, a town in south Lebanon. Many obstacles can be encountered when navigating the path. The ultrasonic sensor with a piezo speaker can notify the blind or blindfolded person about a nearby obstacle. Obstacles can also be detected in real time with real-time SSD video detection built into the android mobile application. Obstacles can be classified into two categories: stationary and moving. Stationary obstacles are those that, by definition,

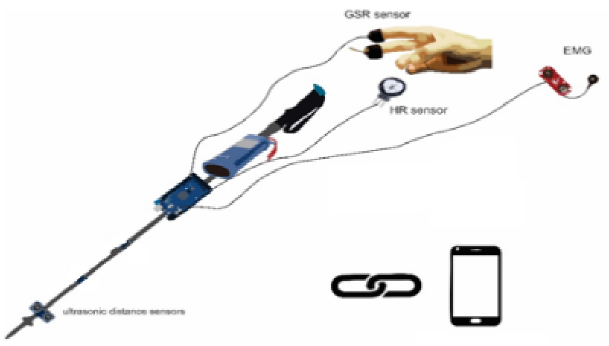

Fig. 1. First prototype of intelligent white cane.

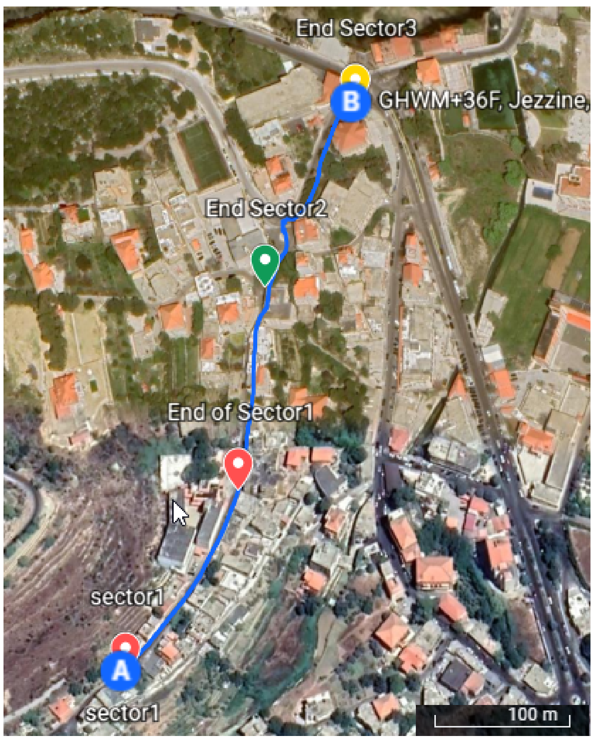

Fig. 2. Experimental path divided into three sectors.

do not move such as parked cars and buses, potted plants, sidewalks, walls, buildings, escalators, while mobile obstacles were cars, motorcycles, pedestrians navigating the route. Some of them are located at the same geographical points from one experiment to another. The number and density of obstacles detected at the starting point were lower than at the middle of the route and at the destination near the city center.

IV. Experimentation Protocol and Collected Data

As described in the previous subsection, the experiment consisted in navigating a route from a residential location to the municipality's public building in the center of the city. The route's infrastructure is not accessible and is not user-friendly for blind users. Six blindfolded people conducted the experiment using the first prototype and six others used the improved BITalino prototype. The six users who conducted the experiment with the second prototype did so more than once but at different times. Most of the users were between 20 and 35 years old, with only two users over 64 years old. The users were all active, healthy, physically fit, and able to walk a path on their legs, not to mention that none of the users had a heart condition. The experiments were conducted in daylight and in cool weather.

For all the experiments, all the users were in a resting state before the start of the test. The preparation time before the start of the test was recorded as was the duration of the entire test for each user. The average time for a user to complete the path and the entire test was around 25 minutes. For the experiments using the second prototype, the path was divided into three sectors named Sector 1, Sector 2, and Sector 3 respectively, which are described in detail hereafter. The total distance of the path from start to finish is about 800 meters and each of the sectors has a distance of about 265 meters. Furthermore, all users been asked to note their stress level within a range from 0 (no stress) to 10 (the most stressed) in each sector three times: at the beginning of each sector, in the middle of the sector and at the end. Similarly, the starting time and the time of passage through the middle of a sector and at the end were recorded. Regarding the three sectors, their respective characteristics are as follows:

- Sector 1 is straightforward road, very large with minimum traffic level and low obstacles density.
- Sector 2 is a straight road, narrower than Sector 1 with a small slope that can be reached at the end, with a medium traffic level and medium obstacle density.
- Sector 3 is quite different, as it is a big slope situated near the center of the city, with heavy traffic level and heavy obstacles density.

A. Dataset

Fig. 3 shows an example of a record obtained at some time during the navigation of a user. For each user, the data stored in database are first extracted in JSON format and then, using Python, converted to CSV format. This conversion allows us to manipulate, visualize and analyze the data properly. The CSV data set for each user can contain more than 1000 records. The number of records for each user depends on the total number of seconds the user took to walk the experimental path. Any series of data recorded over time can be considered as a time series, which is the case of our data which are indexed by the column 'Dates'. A time series can be decomposed into systematic and non-systematic components. Systematic components are level, trend and seasonality, while there is one non-systematic component corresponding to the noise. These components can be defined as follows:

- Level is the average value in the series.
- Trend is the increasing or decreasing value in the series.
- Seasonality is the repeating short-term cycle in the series.
- Noise is the random variation of the series.

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{ "date_user":"26-08-2019 07:27:44
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    "beatvalue" : "54",
    "cm" : "260",
    "conductancevalue" : "218",
    "latitude" : "",
    "longitude" : "",
    "myovalue" : "20"
  }
```


Fig. 3. Example record of the values sensed on a user at a given time.

We tried to decompose several time series for each of the users, each separately. The decomposition was done on the physiological measurements and the distances of the detected obstacles over time. As a result, our time series can be said to have only a trend component. Two variables in the data can be related in three different ways:

- A variable can be the cause or depend on the values of another variable.
- A variable could be lightly associated with another.
- Two variables could depend on a third unknown variable.

V. Analysis of Collected Data

A. Analysis of Data from First (Basic) Prototype

All of the analysis listed below were applied to a single user and to all users who have experimented the first prototype (6 users). The selected user has 1176 records and all users have 7753 records in total. A covariance study was performed on the data to assess the relationship between the distances to the obstacles and each of the physiological measures. Therefore the formula $cov_{x,y} = \frac{\sum(x_i - \overline{X})(y_i - \overline{Y})}{N-1}$ was used, where x_i is a data value of time series X and $\overline{X}$ its mean, y_i and $\overline{Y}$ are similar for time series Y, and N is the number of data samples. The obtained values, which are summed up in Table I, can be analysed as follows. The sign of the covariance can be interpreted as whether both variables change in the same direction (positive) or change in different directions (negative). The magnitude of the covariance is not easily interpreted, but a covariance value of zero indicates that both variables are completely independent. Thus it can be seen that heartbeats and muscle activity change in different direction with the distance from obstacles. Furthermore, it means that when the user is facing a near object (low values of distance from obstacles) heartbeats and muscle activity will have high values.

A problem with the covariance as a statistical tool alone is that it is challenging to interpret. This leads us to the Pearson correlation coefficient which can be used to summarize the strength of the linear relationship between two variables. This coefficient is calculated as the covariance of the two variables divided by the product of their respective standard deviation. It is the normalization of the covariance between the two variables that provides an interpretable score. Indeed, the coefficient has a value between -1 and 1 which represents the limits of the correlation, from a totally negative correlation to a totally positive correlation. A value of 0 means no correlation. The value must be interpreted, where often a value less than -0.5 or greater than 0.5 indicates a significant correlation, and values less than these values suggest a less significant correlation. Table II shows the obtained coefficients and since the correlation values are not greater than 0.5 or less than -0.5, it means that there is no significant correlation between the data. This also means that our data are not related to each other by a linear relationship and one can simply conclude that some of the data are increasing or decreasing together but not in a linear way.

TABLE I
COVARIANCE BETWEEN THE DISTANCES
FROM OBSTACLES AND THE PHYSIOLOGICAL SENSOR MEASURES

single user	Heartbeats	Skin conductance	Muscle activity
Distance from obstacles	-1393.6	618.9	-510.9
all users	Heartbeats	Skin conductance	Muscle activity
Distance from obstacles	-2281.2	831.9	-3763.1

TABLE II
LISTING PEARSON'S CORRELATION BETWEEN DISTANCES
FROM OBSTACLES AND THE PHYSIOLOGICAL SENSOR MEASURES

single user	Heartbeats	Skin conductance	Muscle activity
Distance from obstacles	-0.074	0.13	-0.014
all users	Heartbeats	Skin conductance	Muscle activity
Distance from obstacles	-0.1	0.016	-0.077

Two variables may be related by a nonlinear relationship, such that the relationship is stronger or weaker across the distribution of the variables. Furthermore, those two variables may have a non-Gaussian distribution. In this case, the Spearman's Rank correlation coefficient can be used to summarize the strength of the relation between both variables. Note that this test of relationship can also be used if there is a linear relationship, but may result to output lower coefficient scores.

Table III shows the obtained Spearman correlation coefficients. As with the Pearson correlation coefficient, the scores are between -1 and 1 for perfectly negatively correlated variables and perfectly positively correlated variables, respectively. Instead of calculating the coefficient using the covariance and standard deviations on the samples themselves, these statistics are calculated from the relative rank of the values on each sample. A linear relationship between the variables is not assumed, although a monotonic relationship is assumed (monotonic is a mathematical name for an increasing or decreasing relationship between the two variables).

B. Analysis of Data from Second (BITalino) Prototype

The data were saved and extracted using the same procedure as for the first prototype, only the heartbeat values were extracted for each experiment by Zepp Life, an android mobile

TABLE III
LISTING SPEARMAN'S CORRELATION BETWEEN DISTANCES FROM OBSTACLES AND THE PHYSIOLOGICAL SENSOR MEASURES

single user	Heartbeats	Skin conductance	Muscle activity
Distance from obstacles	-0.19	0.095	-0.1
all users	Heartbeats	Skin conductance	Muscle activity
Distance from obstacles	-0.073	0.17	-0.035

TABLE IV
MEANS OF BIOSIGNALS VALUES FOR EACH SECTOR.

	Heartbeats (mean)	Skin conductance (means)	Muscle activity (means)
Sector 1	99	325.3	510.8
Sector 2	101	364.7	510.9
Sector 3	102	378.8	510.8

application designed and developed by MiFit. As mentioned earlier, six users conducted experiments using this prototype. Each user performed the experiment more than once at different dates and times. The total number of experiments is eighteen.

Several observations can be made according to Fig. 4, 5 and 6. First, the lowest levels for heartbeats, skin conductance and muscle activity values are identified in Sector 1. Second, the values of these three bio signals increment progressively after Sector 1 when navigating into Sector 2 and Sector 3. Note that the data of 13 experiments out of 18 can be interpreted in the same way. It can also be seen from Fig. 4 that the travel time of the sectors increases as one goes along even if all the sectors have the same distance.

The heartbeats, skin conductance and muscle activity values of all users were added together and filtered individually sector by sector. Then the mean value for each of the measures was calculated for each sector and the obtained values are shown in Table IV. There is a notable difference between the sectors with respect to heartbeats and skin conductance values. It can be seen that the lowest means are found in Sector 1, then in Sector 2 and that the highest values are found in Sector 3. Additionally, as previously mentioned, each user has auto-reported his or her stress level at the beginning, the middle and the end of each sector. For each sector and for each user, the highest values of stress reported were taken and added together. Next, the stress level was averaged for each sector, resulting in the values shown in Table V. Clearly, the evolution of heartbeats and skin conductance values are linked to the stress level. Both can accurately reflect the stress level induced by the navigation path.

TABLE V
MEANS OF STRESS LEVELS FOR EACH SECTOR.

	Stress level (mean)
Sector 1	1.8
Sector 2	4
Sector 3	5.6

VI. DISCUSSION

The study and analysis of the data collected during the experimentation made with the first prototype allowed to identify a significant relationship between the distance of the obstacles and the values of the heartbeats and the muscular activity. Both relationships were negatively signed, meaning that these biological signals move in a different direction with respect to the distances from an obstacle. Indeed, a close obstacle means higher heartbeats and muscle activity values, whereas a greater distance from the obstacles means lower heartbeats and muscle activity values.

When experimenting with the second prototype, using a BITalino kit, with an experimental course divided into three sectors and adding self-reporting of the stress level by each user, one found that all physiological measures depended on the distance to the obstacles (heart rate, skin conductivity and muscle activity). Practically, in Sector 1 the users have the lowest values for all the biosignals measures and the lowest stress self-reported stress levels and both the measures and stress levels increase respectively when passing from Sector 1 to Sector 2, and finally from Sector 2 to Sector 3. Adding to the above, even if the sectors have the same distance travel, Sector 1 was traveled the fastest by all users.

All physiological measures and self-reported stress levels, as well as travel times, were found to be related to the characteristics of a sector, namely the density of obstacles and the level of traffic in it. Regarding the path, this one is relatively short since it is about 800 meters long. As for the sectors, Sectors 1 and 2 are straight and even if Sector 3 is a slope, no considerable physical effort is required. In addition, 4 of the 6 users were between 20 and 30 years old.

VII. CONCLUSION AND FUTURE WORK

Getting around on foot is a daily challenge for blind people. Even if they take a familiar route, new obstacles may appear, making no two trips the same and causing stress. We have shown through our experiments with two smart white cane prototypes that stress can be identified and detected when a blind person is navigating a path, and that the stressors causing the stress can be related to obstacles along the path. The data collected can be concretely exploited with machine learning techniques, either to predict the stress of blind people during navigation (regression) or to classify blind people according to whether they are stressed or not at different points of the navigation path (classification). In addition, based on the results of machine learning techniques, we can help blind people to cope with stress or anticipate it in different ways: we can enable blind people to avoid obstacles by vocally informing them about the obstacles and the remaining distance to the point of contact. We can redirect blind people to paths less cluttered with obstacles, we can anticipate stress with small stress-reduction exercises and, if possible, in many more ways. All future work will focus on machine learning techniques applied to the collected data and on approaches to anticipate stress.

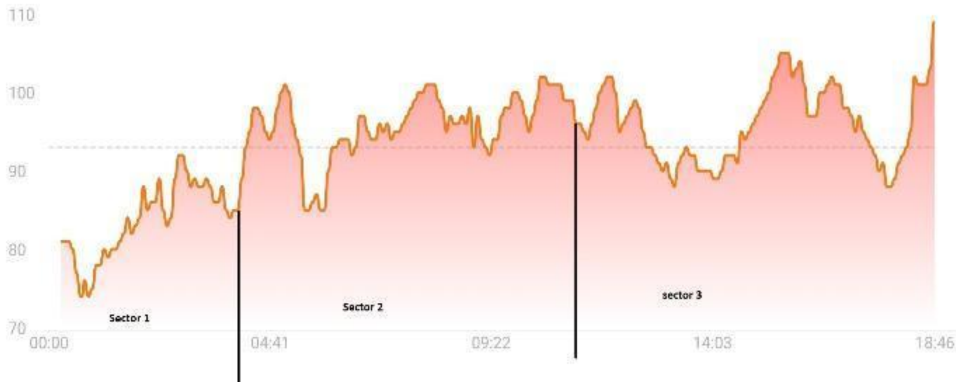

Fig. 4. Image showing heartbeat values over time for a single experimentation for a single user (black lines represent the end of each sector).

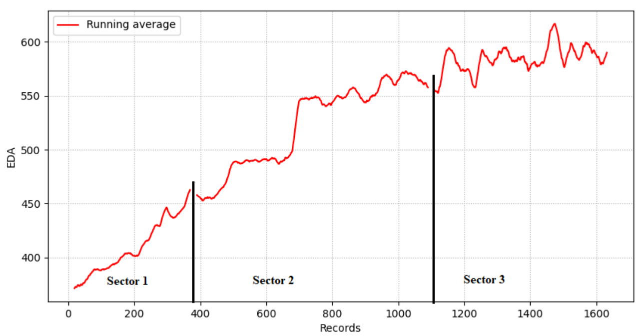

Fig. 5. Image showing running average of skin conductance values for a single user (window=20).

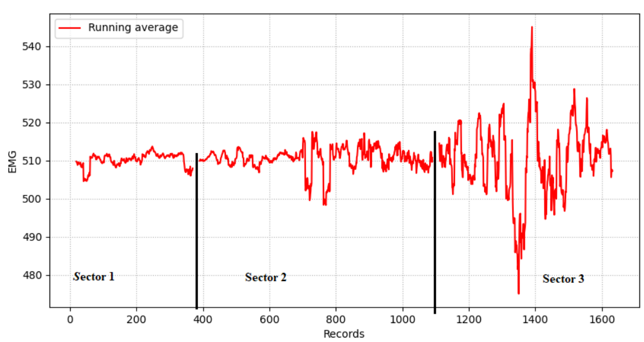

Fig. 6. Image showing running average of muscle activity values for a single user (window=20).

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