User identification using wearable devices

*Acquiring and processing acceleration in a systematic way, ambient temperature, ambient humidity, and other data from smart glasses by Luxottica.

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***Abstract*—During the last decade we have seen the healthcare technology evolve like never before. Technological advancements have been done in wireless communication, MicroElectroMechanical Systems (MEMS) technology has enabled different sensors to be placed around or in the human body for the sole purpose of health monitoring. Different applications or devices that contain integrated circuits have enabled everyone to be able to monitor their vitals in an intelligent way, consuming little to no battery power, all this possible from the Wireless Body Area Network. The aim of WBANs is to simplify and improve speed, accuracy, and reliability of communication of sensors/actuators within, on, and in the immediate proximity of a human body. In this paper we aim to identify a user ,through data related to their gait, collected through monitoring wearable devices and accompanied sensors and devices. Two wearable devices are being introduced in Section I. Our interest in this paper is in human gait and terrain identification.**

***Index Terms*—WBAN, signals, digital signal processing, wearable devices, gait analysis, sensor technology, teltonika, luxottica**

I. Introduction

[1] Wearable technology is becoming more and more usual these days, especially after the Covid-19 pandemic the usage of the wearable devices connected has doubled. Most of the wearable devices in their architecture have an accelerometer or a gyroscope which are the most used sensors in wearable technology. As humans develop new needs, a lot of progress has happened in this kind of devices, and one of the new features involved the gait recognition. The interest for these devices and the data collected and analyzed from them is growing every year, and of course this can help the Healthcare industry. Our paper involves solutions of gathering and analyzing data from two wearable devices developed by Luxottica and Teltonika and we will be further using this data to understand the human gait behaviour.

[3] Global positioning systems are being actively applied to measure static and dynamic displacement responses of large civil engineering structures under different loads. The measurement principle works worldwide, continuously and under all meteorological conditions, and this makes it a very trustworthy to monitor the movement of structures. The goal of the system which possibly can monitor bio-signals and GPS positioning can be based on signal fusion. [2] Although wearable devices are being used for user activity recognition, GPS-based and accelerometer-based (ACC) methods face a lot of different challenges but the most important ones are: low recognition accuracy; coarse recognition capability, i.e., they cannot recognise both human posture (during travelling) and transportation mode simultaneously, and a relatively high computational complexity. User mobility activities that can be recognised include both daily user postures and common transportation modes: sitting, standing, walking, cycling, being a bus passenger or car passenger (including private cars and taxis) and car driver. The novelty of this work is that our approach provides a more comprehensive recognition capability in terms of reliably recognising both human posture and transportation mode simultaneously during travel, by proposing a new sensor method which includes GPS and Foot-Force. In addition, by comparing the new GPS + FF method with both an accelerator method which ensures 62 per cent accuracy, and a GPS as baseline methods, it obtains a higher accuracy which is 95 per cent, with less computational complexity, when tested on a data set obtained from ten individuals.

II. Wearable devices involved in our study

A. *Teltonika product GH5200*

One of the wearable that has these kind of sensors is produced by Teltonika Mobility, which is a company that recently innovated the Worker Badge plus or as it is technically called, GH5200. This device is an autonomous personal tracker with GNSS, GSM and Bluetooth connectivity. It's physical parameters make it fairly easy to carry by the workers. This device has 5 configurable buttons, GNSS antenna (Internal High Gain), Cellular antenna (Internal High Gain), 2.0 Micro-USB, 3 LED indicators, Micro-SIM, e-SIM possibility, 128 MB internal flash memory and it allows up to 5 calls or sms recipients in case of emergency events. It is a smart device which consists on Bluetooth communication for external devices and low energy sensor. The software of this product has a Smart Algorithm of GPRS data sending for GPRS traffic saving, Asset Tracking, Power On/Off event, Event on a Pressed Button, On Demand tracking via button press. The device has a two way communication which makes sure the communication remains efficient and secure. Teltonika is already cooperating with companies like Amman where the worker's safety is highly valuable and as an example as in the

Fig. 1. Teltonika Worker's Smart Badge

event of a fall of more than 1.2 meter the OBC console will raise an alert of different type depending on the user group settings.Also the Geographic Information System page allows the creation of safe zones and their association with one or more group of users. The greatest part of the page is occupied by a Google Map centered on a "default view" (a customised parameter), plus a table view to ease the search and filter of the events on map. Teltonika Worker's Badge device helped us in our study case to measure the speed in one of our scenarios like shown in figure 5, later in this paper.

B. *Luxottica I-see wearables*

I-see glasses are an innovative product and an example of wearable device, which make part of the smart glasses category because they are equipped with sensors like adherence sensor, humidity and temperature sensors, UV light sensor, visible light sensor, led pressure sensor, inertial sensor. These glasses are also equipped with battery and also an off/on button. The UV light sensors shows you through the data recording the over exposure monitoring on your skin and eyes. These glasses record activity and health records that are being measured by the data stream recording. These kind of

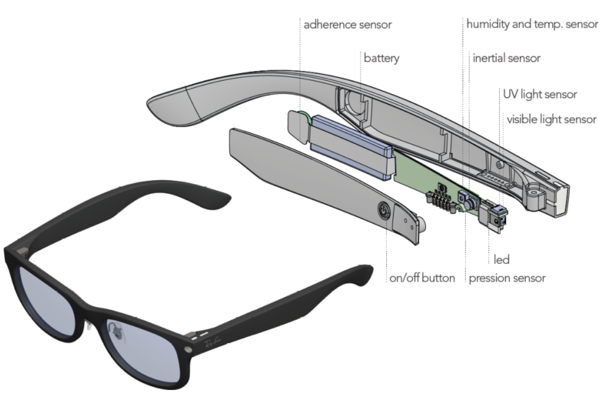

Fig. 2. Luxottica I-see glasses

wearable like most of IoT products can be connected to an application on the mobile phone of the user, providing real time data of every factor that we are interested in. We have designed a diagram that explains all the process of pairing between the glasses and the mobile app. It is quite an easy and simple process where the connectivity is done through bluetooth. Most wearable devices that use WBAN or are used for medical reasons have this kind of connectivity through bluetooth leveraging the emerging IEEE 802.15.6 and IEEE 802.15.4j standards. With this product the user can record

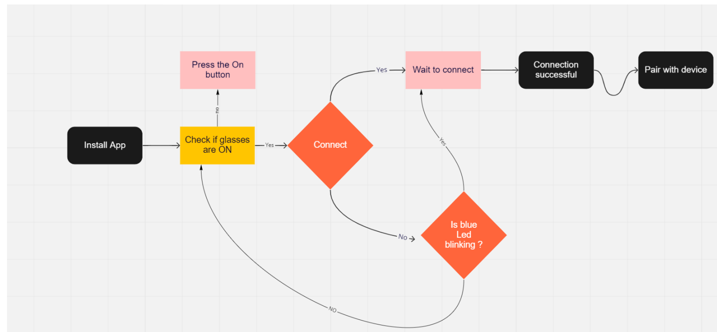

Fig. 3. Diagram that explains the pairing of glasses and app

all the data they need in real time by selecting from the app the sensors they want to activate. The app makes the user understand by analyzing the data behaviors such screen time, number of breaks, and any other activities like sitting, standing, or walking. The glasses will make the difference of the environment if it is indoor or outdoor, based on the temperature and humidity sensors. The app will also keep track of these data and record them until the user exports all the data gathered in a CSV file directly through the mobile app.

Downloading the file with all the data recorded will help to keep track on behaviour of user, analyze more easily and compare through different conditions the behaviour of the person in different terrain, temperature, humidity, location and other different scenario conditions.

III. Proposed Authentication Pipeline

For this study case we propose the pipeline for user identification which has a lot of similarities with other health signals. Each gait cycle has a different duration, which depends on the walking speed and stride length. Considering the accelerometer and gyroscope data collected during a full walking cycle, we remain with variable-size acceleration and gyroscope vectors, which are now expressed in the new orientation invariant coordinate system.

We notice variations in average speed and accelaration patterns in different transportation modes. Speed, in our experiment was measured by Teltonika wearable device and it was used in different conditions according to the table presented below, where we can see that the nature of every signal is different so we need to use different templates and analysis for user identification.

Fig. 4. Authentication pipeline

	Driving bike	Driving Car	Go up Stairs	Go down stairs
Sped	10 km/h	50 km/h	3.5 km/h	5 km/h
Number of picks	Bump	The most smooth	=number of stairs	=smoothing sygnal
n	10050	Range 1200 with x	1400	1200

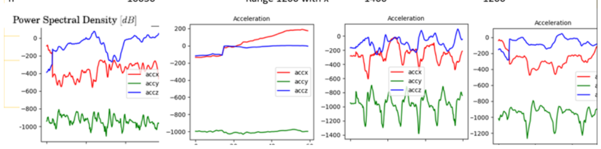

Fig. 5. Comparison of conditions

IV. Our experiment study case

Our study case involved exactly these functions: gathering and analyzing data by collaborating with the I-see glasses. Firstly we gathered the data by doing different activities like walking in different speeds and also different terrains and environments so we generated four different scenarios. We connected the glasses with the app and used them to generate more data, by activating all the sensors we needed. In the mobile application the user can also see a list of all the sensors available, and can select or deselect the sensors they want to retrieve data from. After pairing the glasses, and choosing the sensors we had interest in, we continued to stream raw data. We walked in different terrains, which concluded a river side and a hill. On both main cases there was different terrain difficulty, different environmental conditions and also the speed of walking was different. Following the proposed pipeline, after data acquisition we exported it, in order to analyze it. The data generated in the environment near the river was generated in the same date and time but going in different directions, and also with different speeds. While the data generated from the hill scenario was also generated in the same date and time but the speed was different and also the direction and difficulty of terrain was different since one terrain was offhill and one onhill.

A. Dataset

We have analyzed and processed the data signals for each sensor that we had activated during the experiment in all scenarios. The data that we presented were : acceleration, angular position, environmental, UV light, blue light, the angular velocity and magnetometer. Recent research and machine learning systems have been developed classification of, and analyzing the tracking flexible and adaptive services by using personal information and data such as injuries, terrain, acceleration range,age and gender. Data Set [DS001]

Subject	Age	Gender	Direction	Stairs	Direction	Speed
1	28	Female	Off ill	Ascending	North River	Normal pace
2	25	Female	On hill	Descending	South River	Normal pace

Fig. 6. Dataset of subjects

Th eacceleration data was collected using a smartphone with the customized application to access the accelerometer measurements and to output the data from the sensor to a file (40-50 data points per second for each of the three directions x, y and z). While recording the gait data the phone has been placed in the subject's hand most of the time, data of 2 healthy subjects was successfully recorded on two sessions at two different days with the subjects wearing their usual shoes and walking at normal pace. Subjects were walking straight, but in different directions and terrains like explained further in the paper.

B. Direction identification

During the capture from smart glasses we found a really interesting observation which by a lot of researchers as had a lot of influence in a lot of people in the health industry. Irradiance in this particular case, is well known as the ultraviolet photons (here infere UV radiation) that are absorbed by both the nucleic acid (RNA and DNA) and proteins and are endowed with germicidal properties that are also effective. In particular, about 10Sun position needs to be considered in order to completely explain the direction of the user who was walking. During our experiment we captured a few different gaits in north and south direction along the river since the effects of UV radiations in life processes (with e.g. the UV virucidal effect enhanced in combination with the concomitant process of water droplets depletion because of solar heat and/or reduced in combination with high-humidity because of the larger optical depth).

To get feedback for the UV light, the glasses ambient light sensor (ALS) can be used to measure the light intensity, and with the user's help, the optimum location and orientation so that light energy harvesting can be achieved. Although orientation data is also available from Teltonika device which was involved in the movement.

C. Solar radiation levels are measured in units of W/m2

One difficulty we had during our experiment was that it became difficult to measure light intensity outdoors as there

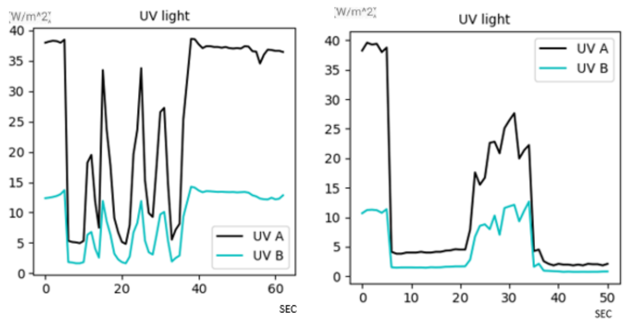

Fig. 7. Comparison of UV light In South and North direction.

were a lot of factors to be considered. One big remark about this graph is that South direction was achieved in 17 meters terrain height, meanwhile the north one in 17 meters in 10 o'clock. There are numerous factors which influence. First of all is the sun activity during this time that have correlation because on south direction our eyes receive slightly more UV light. If we will turn the situation to the opposite and start capture graphs in the same terrain but in another time gap for example 17 o'clock we will see opposite situation with activity of UV light and ambience factor from smart glasses. We also must not forget about different nature condition which may influence the final result also.

Fig. 8. Factors of influence uv light response and terrain of direction identification.

The main objective of this experiment was to use the internal sensors data as an input for the maximum power point calculation. However, a lot of factors were supposed to be considered during the analyze process. If we will know all factors its going to be totally possible to identify the user in order to understand the direction.

D. Angular positioning comparison

Our next experiment was based on different terrain factors, where the difference of height of the terrain was equal to 3 meters between two different users who were going also on different directions, one going towards the top of the hill and the other going down from the hill.

E. Signal pre-processing

Sometimes before analyzing signal from wearable sensors it is a crucial task to understand useful signaling in order to extract error which may have critical influence of outcome. This is an extremely important task for health-related applications. In terms of technology, accelerometers and gyroscopes have received the highest attention in this area, when long-term and personal monitoring is sought: when combined together in an inertial sensor unit, they can be used to automatically and robustly segment the different phases of an activity cycle (generally, a gait cycle) and possibly determine information associated with the quality of each cycle. The temporal accuracy of segmentation techniques can also have an impact on the reliability of the subsequent steps (classification and qualification). For the signal processing first we acquired the Walking data, then we pre-process by doing some procedures like: 1. pre-filtering to remove motion artifacts (Section 3.1), 2. the extraction of walking cycles (Section 3.2), 3. a transformation to move the raw walking data into a new orientation independent reference system (Section 3.3), 4. a normalization to represent each walking cycle (accelerometer and gyroscope data) through fixed length, zero mean and unit variance vectors Different segmentation methods have been used in the past: most common among them are those using a fixed window size and those based on the identification of gait events. Either gait cycles extraction or fixed windows lengths are possible signal segmentation methods. Then the walking cycles are ready to be processed. One limitation of this approach is that if an activity lasts for shorter or longer time periods than the pre-defined chosen window length, the subsequent classification might be affected. When dealing with a physical activity recognition problem, it has been argued that the de-noising of the inertial sensor data is a necessity in order to be able both to extract the relevant information and to identify the gait events from smooth signals which is not our case. In our case we can see

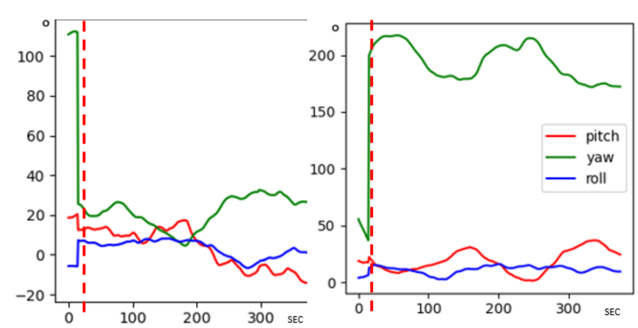

Fig. 9. Segmentation extracting of angular positioning of descend and rise hill

that few microseconds should be avoided because this is quite strange ant not a typical behavioral for this type of signal. This signal could be achieved from user wearing glasses or problem of transmitting signal by bluetooth so this part of the representation should not be considered since its can spoil final result. For further information of our article this error will be not consider in statistic point of view. The purpose of angular analysis to that head will turn as little as possible to achieve a route from A to B. Here the technicalities will be preceded by a case for why applying angular analysis might be a reasonable idea for user recognition. As we can see here

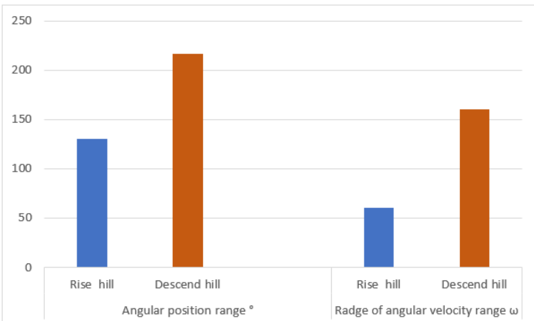

Fig. 10. Fig 4

angular position range when user go down from hill could be recognized by angular position since rising hill is about 35 percentage less in angular position range and 2.5 times less in descend hill. Acceleration was measured using the same data with similar gate and landscape . So we can stand for idea even with same landscape around we can understand the physical effort of person and dors person go on top or going down by acceleration range which is useful in order of differentiate users one from each other if they go through each other.

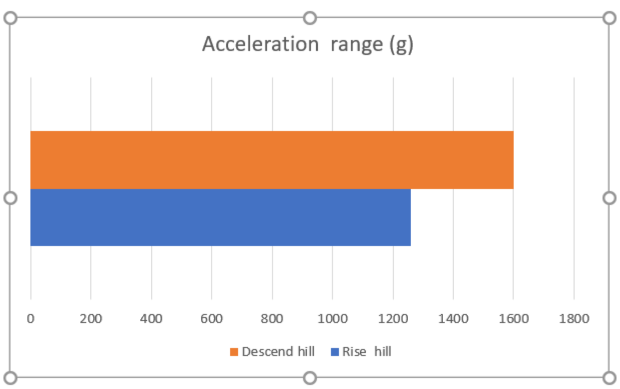

Fig. 11. Acceleration range achieved from hill

V. Methods used for session acquisition

Several acquisition sessions of about a minute were performed for each subject, in variable conditions, e.g., with different shoes and clothes. We asked each subject how they usually move around the cities of Padova or Treviso as they felt comfortable with, to mimic real world scenarios. For the data acquisition, we developed a python algorithm which saves accelerometer, gyroscope and magnetometer signals to be further processed. The magnetometer signal is not used for identification purposes. Below we have presented the plot of the power of accelerometer and gyroscope signals at different frequencies through Welch's method, in this case we suggest setting the Hanning window length to 2 seconds. According to the figure below we followed the window length suggested by Welch's methods which in an ideal scenario is supposed to make the final signal smooth. Most of the signal power is located at low frequencies. The raw inertial signals were acquired using an average sample frequency ranging between 0 and 450 Hz (depending on the conditions around), which is more than appropriate to capture most of the walking signal's energy.

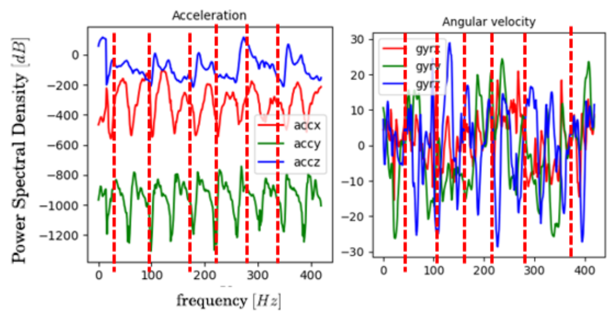

Fig. 12. Power spectral density of accelerometer (Accelaration) and gyroscope (angular velocity) data with proposed Hanning window

At the first block of our processing chain, due to the non-uniform sampling performed by the smart glasses IEEE operating system, we can apply a cubic Spline interpolation to represent the input data through evenly spaced points (200 points/second) and (10 points second). Hence, a low pass Finite Impulse Response (FIR) filter with a cutoff frequency of fc1=80 Hz is used to de-noise and to reduce the motion artifacts that may appear at higher frequencies. In fact, given the power profile of Fig. 10, the selected cutoff frequency only removes noise and preserves the relevant (discriminative) information about the user's motion. An interesting observation we made was that the number of suggested wind is for acceleration and angular velocity is always the same, which means these two parameters strongly depend on each other.

A. *Extraction of walking cycles*

For the extraction of walking cycles we used a template-based and iterative method that solely considers the accelerometer's magnitude signal. This signal is in fact inherently invariant to the rotation of the smartphone and, as such, allows for the precise assessment of walking cycles regardless of how the user wears the device. To identify the template, a reference point in amag(i) has to be located. To do so, we first have to pass pass amag(i) through a low-pass filter with cutoff frequency . As a second step, we need to pick a window of 1 second centered in i, which in Fig. 3 is represented through two vertical blue (dashed) lines. Now, the samples

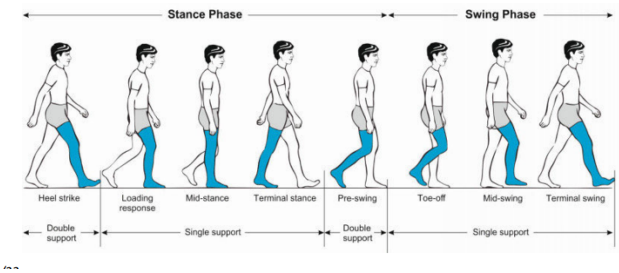

Fig. 13. [7] Phases of gait analysis

of amag(i) falling between the two blue lines defines the first gait template, which we call T, with —T— = Ns samples, where Ns corresponds to the number of samples measured in one second.

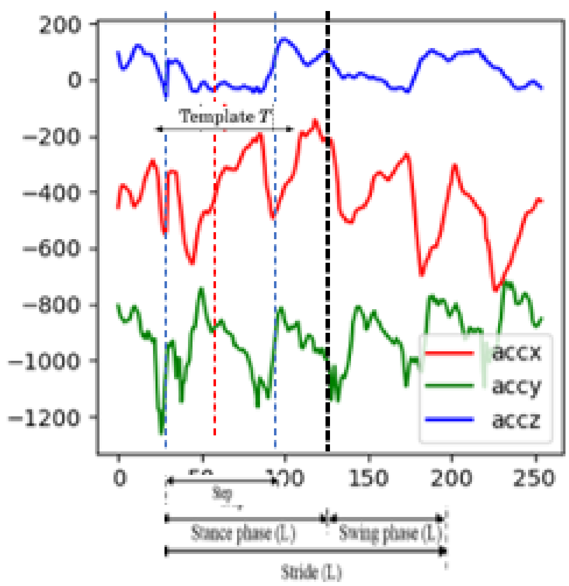

Fig. 14. Template extraction using the accelerometer magnitude amag(i).

The first template is the signal between the blue dashed vertical lines. The red dashed line in the center corresponds to i, the black one is for stance phase identification.The extracted template is then refined in an iterative way and, at the same time, used to identify subsequent walking cycles. To this end, we first define the following correlation distance, for any two real vectors u and v of the same size. So after processing by this algorithm we can normalize the image.

B. Normalization of walking cycles

Each gait cycle differs in terms of duration, due to the different speed which varies during walking, but not in shape. The features extraction phase performed by the CNN requires in input a fixed number of samples for each gait cycle. For this reason each gait cycle is normalized to a length of 10 samples through linear interpolation.

C. Multi stage authentication

All authentication methods involved in this model are used as a second factor of authentication, i.e., in our proposal the user authenticates through the device and in a second step, gives some information to prove that he has possession of certain unique device. The authentication methods used were selected in such a way that they would not change the characteristic of mobility of STT/SC. This was done using common devices, such as smartphones instead of specific cryptographic tokens. [8] The motion data from K = 2 subjects was used to train the feature extractor. A reliable authentication requires fewer than five walking cycles in 80

VI. Conclusions and Future Work

Compared with previous studies, the proposed method can provide information of tracking people in environment which is located in variety of terrain situations. In case if in the near future there going to be opportunity to combine different signal incomes but fusion analysis software with desktop monitor system for mobile applications, this method can reach the mass market because most of the companies searching for safe conditions for their workers. Issues of health monitoring systems (e.g., security, battery life, and sustainable engagement for users) should be solved in the future. The proposed wearable device system which based on GPS tracker speed, acceleration and other healthcare systems require outcome parameters were evaluated on a wide range of gait cycles, positioning in area, obtained in different subjects, and showed good suitability for tracking gait evaluation. Additional studies are needed to further investigate the applicability of this system and algorithm when studying will have bigger database. Nevertheless, the current study makes an important contribution to this field of research because this new system provides different types of income signal, such as blue light response, angular position, environmental information, level of humidity etc. while still maintaining good accuracy and precision for other, commonly used gait parameters acceleration GPS positioning etc. The system can be used as an objective tool in many applications requiring gait evaluation and tracking systems in real conditions. It might prove particular relevance to study monitoring of users real time domain during long-term measurements or to investigate the significance of irregularity during turns for outcome evaluation of medical and rehabilitation interventions.

Regarding user recognition we have shown obvious samples of difference in all the templates we have presented, which can be used for machine learning such a CNN. We were able to differentiate few different templates for different terrains that were taken by two users. As we already saw through the research the smoothing of signal and range are so different and this is a feature that promises to be helpful for user identification.

A. Proposed future work

In future we will analyze the performance on a larger database, allowing a better training. Another open question is whether the training can yield a better generalization in terms of a tolerance against inter-day gait variability when data from several days is used for training. To answer this question a multi-day gait database is needed. Preferably this database will also contain different walking conditions (shoes, underground etc.) to analyse their influence on the recognition performance. In addition, we will focus on a fair comparison of the performance of HMMs and cycle extraction method.

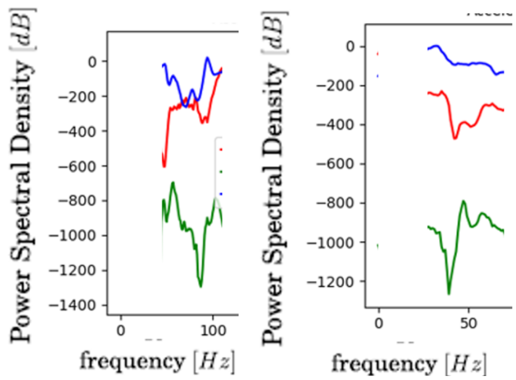

Fig. 15. Walking on stairs - Figure 15 shows in the left presented user 1 walking up the stairs, while in the right it is presented user 2 walking down the stairs.

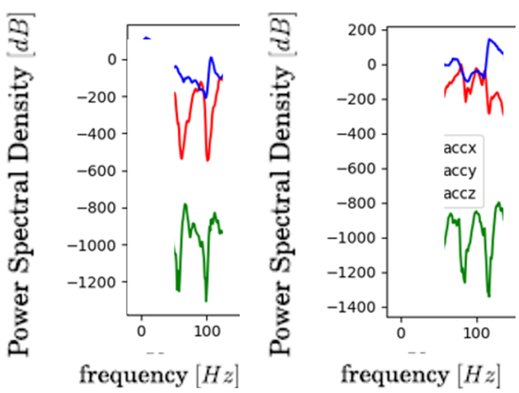

Fig. 16. Walking on hill - Figure 16 shows in the left presented user 2 walking on a hill and on the right the user 2 walking down a hill.

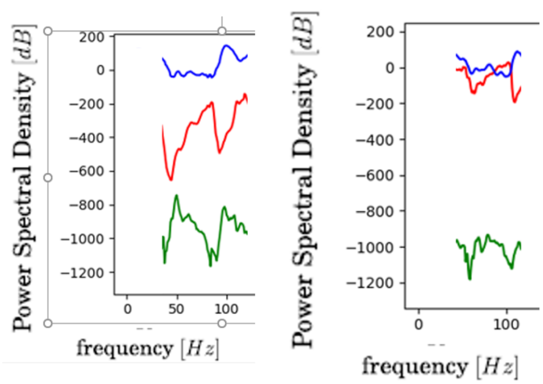

Fig. 17. Walking near river - Figure 17 shows the user 2 walking near a river in the north direction in the left, and in south direction in the right.

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