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Online personal risk detection based on behavioural and physiological patterns

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ABSTRACT

We define personal risk detection as the timely identification of when someone is in the midst of a dangerous situation, for example, a health crisis or a car accident, events that may jeopardize a person's physical integrity. We work under the hypothesis that a risk-prone situation produces sudden and significant deviations in standard physiological and behavioural user patterns. These changes can be captured by a group of sensors, such as the accelerometer, gyroscope, and heart rate. We introduce a dataset, called PRIDE, which provides a baseline for the development and the fair comparison of personal risk detection mechanisms. PRIDE contains information on 18 test subjects; for each subject, it includes partial information about the user's behavioural and physiological patterns, as captured by Microsoft Band©. PRIDE test subject records include sensor readings of not only when a subject is carrying out ordinary daily life activities, but also when exposed to a stressful scenario, thereby simulating a dangerous or abnormal situation. We show how to use PRIDE to develop a personal risk detection mechanism; to accomplish this, we have tackled risk detection as a one-class classification problem. We have trained several classifiers based only on the daily behaviour of test subjects. Further, we tested the accuracy of the classifiers to detect anomalies that were not included in the training process of the classifiers. We used a number of one-class classifiers, namely: SVM, Parzen, and two versions of Parzen based on k-means. While there is still room for improvement, our results are encouraging: they support our hypothesis that abnormal behaviour can be automatically detected.

1. Introduction

Rapid progress in microelectronics and computer systems in recent years has led to the development of sensors and mobile devices with unprecedented characteristics such as low cost, small size, and high computational power [6,20,22,30].

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As a result, there has been rapid growth and development of sensors that can be integrated in mobile phones and wearable devices.

Over the past decade, Vital Signs Monitoring (VSM) and online Human Activity Recognition (HAR) through wearable sensors have attracted considerable interest in a variety of fields, including pervasive and ubiquitous sensing, mobile computing, context-aware computing, and ambient assisted living [1,6,20,21,23,30,34,36,37,43], with special applications in medicine, security, healthcare, entertainment, military defence, and commercial fields [1,6,10,20,22,27,29,30,35–37,43]. Gartner's 2015 Hype Cycle for emerging technologies pinpoints wearables at the peak of inflated expectations [4]. Moreover, firms like Soreon Research have forecasted an annual growth rate of 65% until 2020 for the smart wearable healthcare industry [19].

In this study, we focus on a different but related application of wearable sensors, namely *personal risk detection*. We define personal risk detection as the timely identification of when someone is in the midst of a dangerous situation, for example, a health crisis or a car accident, events that may jeopardize a person's physical integrity. Recently, we deployed a personal security solution based on mobile devices called ELISA[1] (Emergency, Positioning, and Immediate Assistance). ELISA [40] aims at significantly increasing the possibility of quickly locating and assisting a person in the case of an emergency situation, such as kidnapping, car accident, or health crisis. The current number of users is around 750 and growing. When using ELISA, an alarm is triggered manually by the user in case of imminent risk, which is then displayed in an authorized C4 (Command, Control, Communications, and Computers). However, as part of the original design, we envisioned automatic alarm generation by means of a set of wearable sensors that could consider both environmental and user health conditions.

Our ultimate goal is thus to develop a mechanism that is able to detect, in a timely fashion, when an ELISA user is under imminent risk, such as a health crisis or a car accident (for example, a turnover or a high impact crash). Our hypothesis is that a risk-prone situation produces sudden and significant deviations in standard physiological and behavioural user patterns. These changes can be captured by a group of sensors, such as an accelerometer, gyroscope, and heart rate detector.

The aim of this study is twofold. First, we introduce a dataset, called **P**ersonal **RI**sk **DE**tection (PRIDE, for short), which provides a baseline for the development and the fair comparison of risk detection mechanisms. PRIDE contains information of 18 test subjects; for each subject, it includes partial information about user's behavioural and physiological patterns, as captured by Microsoft Band®. Microsoft Band is a network of wearable sensors that monitors 3D acceleration, 3D angular velocity, heart rate, distance, skin temperature, and exposure to ultraviolet rays, among others. PRIDE records include sensor readings of not only when a test subject is engaged in ordinary daily life activities, but also when that subject is in a stressful situation, which may indicate a dangerous or abnormal condition.

We have carefully designed a number of such scenarios, in order to simulate anomalous conditions, comprising possibly risk-prone situations. The scenarios include running 100 m at maximum speed, falling backwards, and more. Further, we evaluated the following detection problem: to build a mechanism that is able to detect, in a timely fashion, when a given user is in a dangerous or abnormal situation, by identifying a clear deviation from the user's ordinary profile of behaviour. Thus, we structure personal risk detection as an anomaly detection problem. The anomaly detector is a one-class classifier, which is not trained using stress scenarios; it is trained only with a user's ordinary conditions data. Stress scenarios are only used to verify if the classifier is capable of identifying them as an anomaly, and not to identify which scenario/activity is being observed. The stress scenarios are thus intended to simulate certain danger or abnormal behaviour; however, we acknowledge they are only an approximation to real-life situations. Our aim is to detect anomalies that can be the result of a car accident, health crisis, robbery, and so on. Since we do not have the means to capture data during a real crisis situation, we decided to undertake this approach.

The second aim of this paper is to show how to use PRIDE to address the above stated anomaly detection problem; to accomplish this, we have tackled risk detection as a one-class classification problem. We trained several classifiers based solely on the daily behaviour of users. Next, we tested the performance of the classifiers to detect anomalies that we did not include in the training process of the classifiers. We tested SVM [41], Parzen classifier [9], and two versions of Parzen based on k-means [13,39]. While there is still room for improvement, our results are encouraging. We have successfully validated our working hypothesis, namely that, a one-class classifier is able to detect anomalies in the sensor information of a test subject, as provided by MS Band, for personal risk detection.

It is worth noting that anomalous situations may sometimes be related to a dangerous situation, *i.e.*, to a personal risk-prone situation. However, tagging a behaviour as abnormal does not always imply risk. Furthermore, not all risk-prone situations always translate into abnormal behaviour, at least with the technology used in this study. In other words, we are able to differentiate abnormal behaviour and ordinary behaviour, thereby detecting some (but not all) possible risk-prone situations.

Paper overview. In Section 2, we review state-of-the-art approaches in HAR and VSM including some applications; additionally, we describe some popular datasets in the area. We also review the main algorithms from the machine learning and pattern recognition domains that are applied to HAR and VSM systems. In Section 3, we describe PRIDE, a new dataset publicly available for personal risk detection. Therein, we briefly describe the procedure to capture test subject data, as well as the mobile application and sensor network used during the process. In Section 4, we present our proposal for

[1] http://elisa-tec.mx

online personal risk detection and the manner in which we use PRIDE for this purpose; we also present experiments using one-class classification algorithms run on the PRIDE dataset. Next, in Section 5, we summarize our main results along with a brief discussion. Finally, in Section 6, we conclude with our findings and comments on future directions of research.

2. Related work

This section outlines state-of-the-art approaches in HAR and VSM, problems that are most related to personal risk detection. First, we present an overview of the key challenges faced by either HAR or VSM. Then, we discuss the types of sensors and how they have been used to capture behavioural and vitals test subject patterns for HAR or VSM. Next, we outline the algorithms that have been used for HAR or VSM, and finally we briefly describe some existing datasets that are often referred to in the literature.

2.1. HAR and VSM: key challenges

Notwithstanding that both HAR and VSM have been hot research areas for more than a decade, they still have several shortcomings. For example, a challenge of HAR is the recognition and labelling of complex activities in daily life situations, especially in a non-laboratory environment [1,20,22,29,30,34,37,43]. According to [1,6,23], a *complex activity* is a group of consecutive movements of single/simple activities performed by a subject under inspection. In the case of VSM, there is a lack of vital samples corresponding to scenarios of crisis that could serve as counterexamples of ordinary, stable conditions. That is, there is a plethora of vitals under healthy or normal conditions; nevertheless, vitals under crisis conditions are sparse and difficult to obtain [30,35]. In addition, expensive computational cost, near real-time classification, resource consumption, among others, are also shortcomings in both HAR and VSM [1,10,21–23,27,29,30,35–37,43].

A key challenge for research communities of both HAR and VSM is the lack of faithful and reliable public datasets [34,37]. In building such a dataset several complexities usually arise. To begin with, it is not easy to recruit volunteers, owing to privacy and anonymity concerns. In addition, openly sharing a dataset of such a kind in to the scientific community requires a proper, legal agreement with the owner of the data [1,22,29,34,35,37]. Even if legal issues are overcome, developing a reliable dataset involves considering technical aspects; for example, one needs to determine the number and type of sensors, how intrusive they would need to be for the application at hand, whether they are user-friendly, where in the body would they be located, how long would the recordings need to be carried out for, and so on and so forth. In addition, the final, intended application must also be taken into consideration, since it is not the same to conduct a study towards mapping vitals to physical activity, as aiming at identifying critical conditions that could represent an imminent risk to the final user [10,29,34,37].

2.2. Sensors for HAR or VSM

During the early studies on activity monitoring and recognition, dedicated wearable sensors such as accelerometers, gyroscopes, and magnetometers were used to recognize a broad number of simple physical activities [36,37,43]. Later, they began using either dedicated sensors attached to the human body and/or sensors integrated into mobile phones owing to their higher availability and low cost [6,36]. As a result, the number and variety of sensors have increased. RFID, GSR, GPS, cameras, microphones, skin temperature, blood pressure, heart rate, EEG, ECG, respiratory rate, proximity, in addition to accelerometers, gyroscopes, and magnetometers, are the most common sensors used across various related studies over the years [1,6,20–23,27,29,30,34–37,43].

There are two main approaches in HAR, one involves the use of external sensors and the other involves the use of wearable sensors. The external approach involves sensors placed in an environment that surrounds test subjects or on specific objects with which subjects interact directly. In contrast, wearable sensors are directly or indirectly attached to the human body [6,22].

Examples of applications of the external HAR approach are typically found in intelligent laboratories and homes [22]. Valedo system, CLARITY Centre, Technology Research for Independent Living (TRIL) Centre, Oregon Centre for Aging and Technology (ORCATECH), University of Florida Gator-Tech Smart House, Georgia Institute of Technology Aware Home, and the Massachusetts Institute of Technology PlaceLab exemplify these smart facilities [3,15,24,30,31,38,44].

Wristbands, smartwatches, and smart clothes such as fitbit©, Basis©, Athos©, and Microsoft©, as well as research projects such as LiveNet, LifeGuard, AMON, MyHeart, WEALTHY, MagIC, and commercial devices like Life Alert, and AlertOne, are examples of applications of the wearable HAR approach [30]. Wearable sensors can be obtrusive or unobtrusive, depending on the way they attach to the human body. Sensors that adhere to the human body are considered obtrusive. On the other hand, sensors embedded in clothes, eyeglasses, belts, shoes, wristwatches, wristbands, headbands, mobile devices, and so on, are considered unobtrusive [6,20,36].

HAR studies focus on the recognition of any kind of human activity; however, only a limited list representing complex human activities prevails in several works [1,6,10,20–23,27,29,34–37,43]. Examples of such activities are as follows: prepare and consume food, personal hygiene, such as taking a shower and brushing teeth, household chores, physical exercise, driving, walking, sitting, lying down, climbing stairs, interacting with personal objects, etc.

Liming Chen et al. [6] surveyed state-of-the-art research on sensor-based activity recognition, and provided a high-level overview about approaches and methods associated with sensor-based activity monitoring, modelling, and recognition. Furthermore, they compared different methods based on their robustness in real-world conditions and real-time performance. Roggen et al. [34] described datasets that contained complex activities often found in the literature; they also provided their own dataset with environment and wearable sensors, highlighting their use to develop new sensor networks and machine learning techniques for human activity recognition systems. Liu et al. [23] addressed the problem of complex activity recognition using time series extracted from multiple sensors, by representing single/atomic activities as a dictionary of time series patterns called shapelets; they evaluated their approach using two datasets from the literature and one developed by them. In addition, a comparison with classifiers commonly used for both atomic and complex activity recognition is given. Soumya et al. [10] implemented a wireless sensor network for activity recognition focused on healthcare; three activities are identified, sitting, walking, and standing, with 81% accuracy using a low-energy flex sensor band worn on the knee.

Lara and Labrador [22], and Mukhopadhyay [27] surveyed the state-of-the-art in HAR with regard to wearable sensors; they compared HAR systems in terms of learning approach, types of sensors (obtrusiveness, wearables, etc.), monitoring activities, and detection accuracy. In their survey, they mention the work of Stikic et al. [37], where different directions are proposed to bridge the gap between state-of-the-art activity recognition approaches and real-world deployment of activity recognition systems; they built an unobtrusive activity recognition system that requires minimal user involvement in the training process.

Patel et al. [30] summarized recent developments in the field of wearable sensors and systems that are relevant to the field of rehabilitation, describing applications focused on health and wellness, safety, home rehabilitation, treatment efficiency, and early detection of disorders. Selvaraj [35] investigated the effectiveness of patch sensors for continuous and long-term monitoring in older subjects over 50 consecutive days at their home setting; results confirmed that patch sensors are suitable for long-term vital sign monitoring as they achieve high accuracy measurements and positive user feedback for home use. Lamprinakos et al. [21] described the design and implementation of a platform that integrates vital signs monitoring (Telehealth) with behavioural analysis based on home care sensors (Telecare) aimed at improving the quality of life of elderly people and reducing healthcare costs. Moreover, the platform enables the deployment of services to follow up with a patient's health status based on a set of monitored parameters per disease and diagnoses deviations from their usual activities. Avci et al. [1] surveyed the current research directions of activity recognition using inertial sensors (such as gyroscope and accelerometer), with potential application in healthcare, wellbeing, and sports. Shoaib et al. [36] reviewed the main works that implement HAR systems on mobile phones using only their built-in sensors.

2.3. Main algorithms and techniques used in HAR and VSM systems.

Pattern recognition and classification algorithms are the most relevant processes in HAR and VSM systems. A wide range of machine learning techniques have been used to manipulate data, find patterns, and classify them, which implies labelling data according to an activity. The learning techniques are classified as supervised and unsupervised. Supervised learning handles labelled collected data, whereas unsupervised learning deals with unlabelled data [6,20,22,27,37]. References [1,6,20,22,23,27,29,37,43] list the most common classification algorithms used in HAR literature . Additionally, Shoaib et al. [36] presented a survey of the main classifiers implemented on mobile phones. The following algorithms are frequently mentioned: decision trees, Bayesian networks, k-nearest neighbours, support vector machines, fuzzy logic, regression methods, Markov models, classifier ensembles (boosting and bagging), artificial neural networks, etc.

Regarding VSM, in [7,16,18,28,32,33], different algorithms and techniques such as Kalman filter, hidden Markov models, autoregressive hidden Markov models, Gaussian models, Rao-Blackwellised particle filtering, templates, thresholds, spectral analysis, fuzzy logic, and artificial neural networks are applied.

2.4. Existing datasets

Across the literature, there are few public datasets suitable for complex activity recognition, while there are plenty that address the recognition of specific activities.

Existing datasets in VSM comprise very precise and dedicated sensors from the medical domain such as electrocardiograms, pulse oximeters, and respiratory rate sensors, to mention some. Even though there are some open datasets, their purpose is mainly oriented to register medical conditions such as arrhythmia, hypertension, surgical care, coronary care, and neonatal care, among others.

Below, we describe some of the datasets that align with our research interest. The reader is referred to the original work for more detail.

2.4.1. MIT PlaceLab datasets

The PlaceLab is a live-in laboratory in Cambridge, for the study of ubiquitous technologies in home settings. It is a joint MIT House and TIAX initiative. Their principal datasets are PLIA1 (PlaceLab Intensive Activity 1), PLIA2 (PlaceLab Intensive Activity 2), and PLCouple1 (PlaceLab Couple 1). Even though PLIA2 is an improvement of PLIA1, PLCouple1 is the more active and richer dataset among the three; hence, we describe it next.

PLCouple1 contains data of a couple that lived in the PlaceLab for a period of 10 weeks, with approximately 206 ambient sensors placed around the laboratory environment, 277 motion detection sensors, 435 RFID tags, and 5 wearable sensors. In addition, the laboratory has audio-visual recordings that are not publicly available due to privacy issues.

In addition, there are 100 h of labelled activities, making a distinction between "foreground" and "background" activities. "Foreground" activities are those the test subject pays full attention to when performing the activity. In the other case, the activity is considered "background". Activities were fined-grained, for example, sweeping, folding laundry, brushing teeth, actively watching TV, and watching TV in the background.

Although the dataset is very rich in sensor measurements, there are some limitations the authors are aware of. Data collection in a laboratory environment, only 104 h of marked activities, missing interesting activities such as sleep and personal hygiene, test subjects participating in simultaneous experiments requiring wearable sensors, and a small amount of test subjects, are examples of these limitations. The PLCouple1 dataset has been used in several works, including [3,15,24,31,38,44].

2.4.2. TU Darmstadt dataset.

Developed and introduced by Huỳnh et al. in [14]. The dataset consists of seven days of recording, 84 h of effective labelled data, one male test subject, two wearable accelerometer-based sensors, and 20 activities. The types of activities recorded are: eating, washing dishes, personal hygiene, walking, driving, sitting, standing, etc. The rest of the activities are unlabelled.

Despite the fact that the TU Darmstadt dataset faces constraints such as the number of test subjects and the number of wearable sensors, it contains a reasonable amount of effective hours and an extensive range of single activities that can be translated into complex ones. Furthermore, data was also collected under real world conditions.

2.4.3. The OPPORTUNITY activity recognition dataset.

Roggen et al. [34] contributed with an extensive complex dataset that has been a benchmark in the HAR field. It consists of 12 test subjects, 72 sensors, around two hours of effective data per subject, approximately 27,000 labelled interactions, and a total of 25 h of sensor data. Multiple sensor systems were deployed on objects, in the environment, and on the body of test subjects.

According to the authors, the dataset aimed at maximizing the number of activity instances that were collected, while keeping the execution naturalistic. However, the activities were recorded in a laboratory environment, namely in a room that simulates a flat studio with a deckchair, a kitchen, access doors to the outside, a coffee machine, a table, and a chair. Test subjects performed activities of daily living such as lying on the deckchair and getting up, moving around the room interacting with objects, walking outside the laboratory, preparing and eating food, drinking coffee, cleaning up the table and washing dishes, opening and closing different furniture and household electrical appliance, etc.

The dataset contains rich gestures instances and annotations. However, it presents some limitations; for example, natural body movements and interactions with objects are restricted by consecutive repetitions within a short period of time; moreover, the test subject must follow a given sequence of activities, and finally, all recordings are performed in a laboratory environment.

2.4.4. The MHEALTH dataset

Banos et al. describe the dataset in [2]. It is built from body motion and vital signs of 10 test subjects with diverse profiles, 12 activities, and three wearable sensor devices. The sensors are 3-axis gyroscopes, 3-axis magnetometers, 3-axis accelerometers, and an electrocardiogram. The recorded activities are: standing still, sitting, lying down, walking, climbing stairs, waist bends forward, frontal elevation of arms, crouching, cycling, running, jogging, and jumping.

The test subjects performed each activity in independent sessions. Some activities were recorded in sessions of one minute and others during repetitions of 20. Despite the guided recording, the dataset was captured in a non-laboratory environment that offered the test subjects the freedom to perform the activities naturally. Limitations of the dataset are the number of sensors used, as well as the scarce time for activity execution, which led to a limited number of recordings.

Existing datasets as the ones just described, when available to the research community, have been of great support in the development of new techniques and applications. We believe that a dataset should avoid data collected in a laboratory environment and/or with the presence of a third person that could lead to unnatural behaviours during the execution of an activity as far as possible. In addition, whenever possible, the use of obtrusive wearable sensors for long periods should be avoided. Additionally, it is desirable that a dataset contain more effective hours of labelled and/or unlabelled data.

3. Building a new dataset: the PRIDE dataset

As mentioned earlier, our aim is to distinguish any non-ordinary condition or risk-prone situation from normal behaviour; therefore, our work cannot explicitly classified as either HAR or VSM. It is not HAR since we are not pursuing the recognition of a user activity, and it is not VSM, since we are not using specialized medical sensors (indeed, we monitor only heart rate). This is one of the reasons we decided to undertake the creation of a new dataset, based on ordinary life activities complemented with specific scenarios under stressful situations. However, algorithms and techniques used in HAR and VSM systems (summarized in Section 2.3) are well suited to our case, which can be stated as an anomaly detection problem, where one-class classification algorithms have proved effective. As explained later in Section 4, we decided to perform our classification experiments using the following techniques: support vector machines, Parzen, and two versions of Parzen based on k-means. Next, we describe the methodology employed to build such a dataset.

3.1. Building the dataset

The PRIDE (Personal Risk Detection) dataset is built with the help of 18 test subjects and a period of data collection of one week each, 24 h per day; the normal conditions dataset (NCDS) is built in this manner. Next, to build the anomaly conditions dataset (ACDS), the same 18 test subjects collaborate in another process to gather data under specific abnormal or stressful conditions. The scenarios include activities such as running several meters, going up and down the stairs of a several-floor building as fast as possible, simulating a fight, and so on.

The NCDS also includes 14 labelled activities such as having breakfast, having lunch, having dinner, drinking coffee, driving a car, watching TV/going to the cinema, sleeping, riding a bike, jogging, running, a social gathering, using public transport, and gym (anaerobic activity, *e.g.* weight lifting, sprinting). Additionally, an extra field was included, so the test subject could label any other activities of interest. However, in the present study, we do not attempt to recognize any of these activities.

To collect data we use Microsoft Band© and a mobile application that we developed using the available SDK. We captured data from test subjects under normal and abnormal conditions. All captured stream data is transferred to a private cloud under our administration.

During the period of data collection, each test subject registers their daily life activities under real world conditions. Hence, their behaviour and vital signs are not restricted to a laboratory environment. For this reason, the dataset provides real data under real daily situations, where the test subjects feel comfortable wearing the band [35] and without being deprived of their privacy [10].

To ensure a more complete study [22], test subjects with diverse characteristics such as gender, age, height, and sedentary lifestyle were considered. The test subjects group comprises 5 female and 13 male volunteers with ages between 21 and 52 years old, heights from 1.56 m to 1.86 m, weights ranging from 42 to 101 kg, exercising 0–10 h a week, and time spent sitting during working hours or leisure from 20 to 84 h a week.

To build the anomaly dataset, we designed five specific scenarios that simulate abnormal or stressful conditions. These scenarios were carefully planned and included the following activities: rushing 100 m as fast as possible, going up and down the stairs of a several-floor building as fast as possible, a two-minute boxing practice, falling back and forth, and holding one's breath for as long as possible. Each activity, respectively, aims at simulating a real-world dangerous or abnormal condition: running away from a danger situation, leaving a building owing to an evacuation alert, fighting back an aggressor during a quarrel, swoons, and breathing problems like dyspnoea.

In order to obtain reliable results that serve to distinguish abnormal from normal conditions, the scenarios are monitored without interfering with test subjects concerning their freedom to perform such activities. The special session to build the anomaly dataset lasts for about two hours and demands considerable physical effort. Although the elderly are a very important group in society as pointed out in [21], we cannot include them in the process to collect data owing to the demanding nature of our methodology.

As mentioned in Related Work, Section 2, activities such as running, climbing stairs, and falling have been successfully detected by accelerometers and gyroscopes [1,6,10,22,23,27,29,30,34–37,43]. We believe that other abnormal events originating from situations such as a fight or loss of consciousness, can be detected with the same set of sensors.

A day log from a test subject includes all observations that appear from 00:00 h to 23:59 h. Even though a test subject gathered data for a period of seven days, there is a gap in the log of at least 40 min normally three times per day owing to the battery recharging process. Moreover, since the collection of data is performed during ordinary and quotidian life, test subjects normally paused data collection for several personal reasons, *e.g.*, to perform an aquatic activity.

PRIDE is freely available for download, through Syncplicity©cloud solution, by sending a request to the corresponding author. For the interested reader, we show in Annex 1 from the PRIDE dataset, the mean value, $\bar{x}$, and the sample standard deviation, s, of all test subject features as well as the number of observations.

In the following, we briefly describe the mobile application developed as well as the band's built-in sensors.

3.2. Mobile application and sensor network description

To capture test subject data, we decided to use Microsoft Band [25,26], mainly for two important reasons: first, the number and nature of sensors included in the band; and second, the availability of an SDK that allows us to develop an application according to our needs. The application we developed for Android platform connects to the band via Bluetooth. It then reads the sensor data in real time and stores all measurements into a CSV file that resides in the mobile phone. The file is transferred to a secure FTP server under our administration. This is done by the test subject once or twice a day, using the *Upload File to Server* option on the application.

Accelerometer and Gyroscope data is read at an interval of 125 ms (sensors operating frequency set to 8 Hz), in order to ensure a reasonable file size (about 175 MB) after 24 h and a battery life of almost 9 h. The battery can be recharged to 80% of its full capacity in approximately 40 min. To compare, if we use a sensor operating frequency of 31 Hz or 62 Hz, the size of the file grows up to 650 MB and 870 MB, respectively, and battery life is degraded to 8 h and 6 h, respectively. However, the frequency of operation can be set to 8, 31 or 62 Hz any time directly from the application. Distance, heart rate, pedometer, and calories measurements are logged using a readout interval of 1 s, while UV and skin temperature data are collected every 60 s and 30 s, respectively, or whenever the value changes. Since GPS data is not available using the

Table 1
Sensor description.

Sensor	Description	Frequency
Accelerometer	Provides X, Y, and Z acceleration in g units. 1 g = 9.81 m per second squared (m/s^2).	8 Hz
Gyroscope	Provides X, Y, and Z angular velocity in degrees per second, (°/sec) units.	8 Hz
Distance	Provides the total distance in centimeters, current speed in centimeters per second (cm/s), current pace in milliseconds per meter (ms/m).	1 Hz
Heart rate	Provides the number of beats per minute, also indicates if the heart rate sensor is fully locked on to the wearer's heart rate	1 Hz
Pedometer	Provides the total number of steps the user has taken.	1 Hz
Skin temperature	Provides the current skin temperature of the user in degrees Celsius.	33 mHz
UV	Provides the current ultraviolet radiation exposure intensity (none, low, medium, high, very high)	16 mHz
Calories	Provides the total number of calories the user has burned.	1 Hz

SDK, it is important to mention that distance is derived by a Microsoft proprietary algorithm, which takes into consideration the number of steps taken by the user (pedometer), and user's stride length and height. Height and other general user information is provided when setting up the application and when synchronizing with the band for the first time. The algorithm is a Microsoft patent.[2]

In Table 1, we list and describe the sensors in the band as well as the frequencies at which data can be retrieved from them. Using the shown sensors operating frequencies, test subject data grows to approximately 1,670,160 registers in a day (around 175 MB) and battery life is about 9 h.

4. Proposal for online personal risk detection

In order to detect a personal risk situation, we use an approach based on the rationale that people usually behave based on the same behavioural and physiological patterns or with small variations thereof. To support our claim, we use the PRIDE dataset to develop a personal risk detection mechanism, but before running any experiments, we first performed pre-processing on the dataset. The following steps summarize the dataset pre-processing procedure:

- For each test subject in the PRIDE dataset, the data collected is arranged by day.
- Date and activity label features are removed.
- The feature vector is computed using a window size of one second. Because the frequency of our sensors varies significantly, we apply three rules to compute the feature vector of a given window: 1) if the readout interval is less than one second, the feature vector is assigned both the average and the sample standard deviation for all the sensor measurements; 2) if it is equal to one second, then the feature vector is directly assigned the sensor value, and 3) if it is greater than one second, the feature vector is assigned the last sensor value.

More specifically, a feature vector for a given window contains:

- Mean and standard deviation for gyroscope and accelerometer measures.
- Absolute values of heart rate, skin temperature, pace, speed, and UV sensors.
- The incremental change (Δ-value) for absolute values of total steps, total distance, and calories burnt. A Δ-value is computed as the difference between the current and previous one.

As a result, a 26 dimensional feature vector is obtained and its values refreshed every second. The structure of the vector is shown in Tables 2 and 3. Both, the NCDS and the ACDS are pre-processed using this method. Next, we proceed with the description of several experiments that support our hypothesis that abnormal behaviour can be automatically detected using a one-class classification approach [17].

We divided each of the test subject logs into 5 folds to use them in a five-fold cross-validation. In the cross-validation, we used 4 folds of the test subject normal behaviour for training and one fold, joined with the anomaly dataset log, for testing the classifiers. We repeated this procedure five times alternating the test subject fold that is left for testing. Accordingly, we created 5 training datasets and 5 testing datasets.

[2] Adaptive Lifestyle Metric Estimation. Microsoft internal number: 341468. US Patent 20150345985-A1

Table 2
Feature vector structure (1–18 fields).

Gyroscope accelerometer						Gyroscope angular velocity						Accelerometer					
X axis		Y axis		Z axis		X axis		Y axis		Z axis		X axis		Y axis		Z axis	
$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18

Table 3
Feature vector structure (19–26 fields).

Heart rate	Skin temperature	Pace	Speed	UV	Δ Pedometer	Δ Distance	Δ Calories
19	20	21	22	23	24	25	26

In our datasets (the pre-processed PRIDE dataset), every object is stored as a row in a CSV file, following the structure of the feature vector described previously. The last column of every row contains one of two labels ("typical" or "atypical"). The label "typical" indicates that the object represents normal test subject behaviour, and the label "atypical" indicates that the object represents an anomalous state. This label, though, is never used for method training, but only for computing the method detection performance.

Users want to be protected by the ideal classifier, namely, the one that is able to detect every possible abnormal behaviour without confusing for normal behaviour. Therefore, our task is to build classifiers that maximize true positive classifications (*i.e.* true abnormal conditions) while minimizing false positive ones (*i.e.* false abnormal or dangerous situations). Therefore, we evaluated the classifiers using the following performance indicators:

- **Precision - Recall (P-R) curves**: Precision is the fraction of retrieved instances that are relevant, while Recall (also known as sensitivity) is the fraction of relevant instances that are retrieved. In our case, a relevant instance is characterized by a true anomaly. In addition, Recall is equivalent to the true positive detection rate (TPR). We built a P-R curve for each user independently and a single P-R curve from mean and standard deviation of all users.
- **ROC curves**: We computed the performance indicators from Receiver Operating Characteristic (ROC) curves, which we built according to [11]. We followed a similar approach as in the P-R curves. We built a ROC curve for each user independently and a single ROC curve from mean and standard deviation of all population. In the context of personal risk detection, sensitivity is crucial, *i.e.*, it is preferable to receive several false alerts (false abnormal or dangerous situation) than missing one true (false ordinary or normal condition); hence, it is important to maximize Recall even at the cost of experimenting a certain false alarm rate.
- **AUC**: Area under the curve of true positive detection rate (TPR) versus false positive detection rate (FPR). This indicator gives an idea of the general performance of the classifier for all false positive detection rates.
- **EAR**: Equal Accuracy Rate is the value of the true positive detection rate when it is equal to the true negative (*i.e.* normal test subject behaviour) detection rate (TNR). This value represents the best trade-off between the two types of metrics TPR and TNR. This measure might not be of interest in the present context of personal risk detection; however, we have not excluded it here, as it offers a complementary perspective of detection performance.
- **Accuracy**: The number of correct classifications (true positives plus true negatives) divided by the total number of classifications made.

In order to create a baseline for future researches, we evaluated the following classifiers:

- **Parzen**: Parzen Window Classifier using Mahalanobis distance [9]. For every training dataset, we computed the width of the Parzen-window averaging the distances between objects sampled every 60 s.[3]
- **k-means1**: A version of Parzen Window Classifier based on k-means [39]. k-means1 classifies new objects based only on the closest centre of cluster.
- **k-means2**: A version of Parzen Window Classifier based on k-means [13]. k-means2 classifies new objects using all centres of clusters.
- **ocSVM1**: The implementation of one-class Support Vector Machines [41] included in LibSVM [5] with default parameter values ($\gamma = 0.038$ and $\nu = 0.5$) and using the radial basis function kernel.
- **ocSVM2**: A version of ocSVM1 with a pseudo-exhaustive algorithm that maximizes max(TPR+TNR). First, we fixed $\nu = 0.01$ and, starting with $\gamma = 0.0$, we increased γ by 1.0 until max(TPR+TNR) did not increase in three consecutive iterations. Then, we iterated over five values near the best γ found and for each iteration, we tested five different values of ν in [0.1, 1.0]. If max(TPR + TNR) did not increase after trying two consecutive values of ν, we increased γ and started with the values of ν all over again. We repeated this procedure 10 times, each time testing values closer to the best γ and ν. It is worth mentioning that this optimization was performed on the testing dataset, with the sole intention of demonstrating the performance of SVM, with fine-tuned parameters set up.

[3] This procedure saved approximately 7 days of computing distances per test subject in an Intel Core i7-4600M CPU at 2.90 GHz.

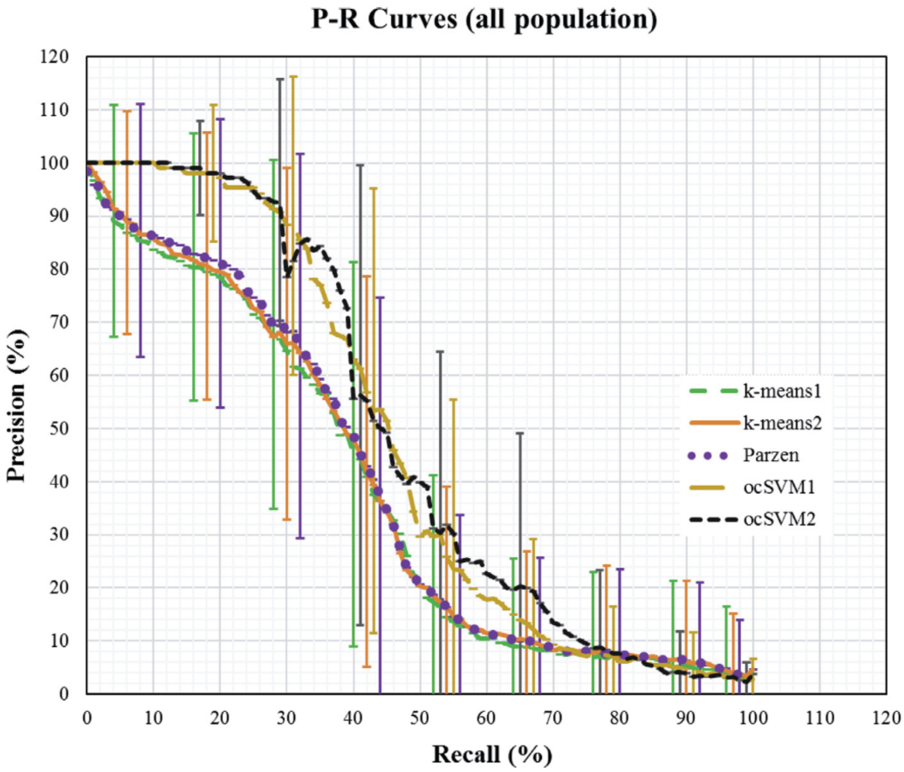

Fig. 1. Precision-Recall curves built from mean and standard deviation of all users.

5. Results and discussion

In the previous section, we showed how to use PRIDE to develop a personal risk detection mechanism and found encouraging results. We trained several classifiers based only on the daily behaviour of users; then, we tested their performance to detect anomalies. The experiments supported our hypothesis that abnormal behaviour can be automatically detected using a one-class classification approach.

For the sake of simplicity and space, we only show the P-R and ROC curves of all population in Figs. 1 and 2, respectively; standard deviation is shown as a vertical line per algorithm at different intervals. For those seeking further detail, individual P-R and ROC curves can be viewed through Syncplicity©cloud solution, the same way as the PRIDE dataset.

From P-R curves shown in Fig. 1, we can point out that ocSVM1 and ocSVM2 outperform the three Parzen methods; this is confirmed by the ROC curves analysis below. We also notice that all classifiers attained above 80% of Recall at the cost of a very high false alarm rate, above 90%, since Precision is lower than 10%; percentages provided are the average values of all population.

ROC curves in Fig. 2 show that ocSVM1 and ocSVM2 achieved the highest values of TPR for FPR between 0% and 20%; here again, percentages are the average values of all users. For values of FPR higher than 20% the performance of ocSVM2 drastically drops. The curves also show that ocSVM2 exhibits the highest standard deviation; hence, we performed a more exhaustive analysis to study the particular performance of the algorithms for each user. Tables 4–6 show that ocSVM1 achieved the best performance for most of the test subjects (the best result by test subject is shown in bold typeface). Surprisingly, the optimization of ocSVM2 according to max(TPR+TNR) did not boost its performance, which leads us to believe that multi objective optimization could be required.

To further study the differences among the algorithms, we applied the Friedman test [8] and the Bergmann-Hommel dynamic post-hoc [12]. We compared the results considering a level of significance $\alpha = 0.05$. We used *Critical Difference diagrams* (CD diagrams) [8] to show the post-hoc results because CD diagrams compactly present the rank of the algorithm according to one performance indicator. CD diagrams also show the magnitude of differences between algorithms and the significance of the observed differences [8]. In a CD diagram, the rightmost algorithm is the best algorithm, while the algorithms sharing a thick line have statistically similar behaviours. CD diagrams in Fig. 3 show that ocSVM1 achieved the best average ranking; however, there is no significant difference compared with the rest of the algorithms for most of the performance indicators. With regard to accuracy, ocSVM2 and ocSVM1 achieved the best results and their performance is significantly better than the rest of the algorithms.

Table 4
Area (in percentage) under the curve of TPR versus FPR.

Test subject	Parzen	k-means1	k-means2	ocSVM1	ocSVM2
TS1	94.4	92.7	94.4	97.3	**97.8**
TS2	93.3	92.5	93.4	**94.5**	87.5
TS3	**88.3**	87.4	**88.3**	87.4	85.0
TS4	85.0	**88.0**	84.8	83.9	82.2
TS5	88.9	84.4	**89.0**	80.8	79.6
TS6	95.0	93.1	95.1	96.1	**97.9**
TS7	76.3	**78.7**	76.2	69.4	67.3
TS8	90.3	89.6	90.3	**93.8**	86.6
TS9	89.4	88.4	89.8	**95.3**	90.9
TS10	89.9	84.4	89.9	**94.0**	92.2
TS11	90.1	88.5	90.1	**93.4**	90.6
TS12	79.7	**80.0**	79.4	74.6	75.9
TS13	**84.7**	84.3	84.3	75.8	62.5
TS14	**79.9**	75.0	**79.9**	78.0	79.1
TS15	91.6	90.8	91.6	93.8	**94.0**
TS16	**87.0**	86.3	**87.0**	83.2	77.0
TS17	92.8	90.7	92.8	**98.1**	97.9
TS18	88.7	87.0	88.8	**89.1**	87.0

Table 5
Equal accuracy rate: the value of TPR (in percentage) when TPR = TNR.

Test subject	Parzen	k-means1	k-means2	ocSVM1	ocSVM2
TS1	86.1	82.2	86.0	91.7	**94.3**
TS2	85.4	84.3	85.5	**85.6**	83.8
TS3	**81.5**	79.2	81.3	78.8	78.9
TS4	80.6	**81.8**	80.4	75.5	76.2
TS5	83.2	75.5	**83.6**	70.7	72.0
TS6	86.0	83.6	86.2	88.7	**93.9**
TS7	70.9	**71.4**	70.5	64.7	62.2
TS8	80.2	80.1	80.2	**85.3**	78.3
TS9	79.7	77.7	80.3	**90.0**	86.2
TS10	80.6	73.7	80.6	**87.8**	84.3
TS11	81.3	77.2	81.4	83.8	**84.4**
TS12	**71.3**	69.3	71.1	66.8	70.5
TS13	74.8	**75.1**	74.6	66.9	56.1
TS14	72.9	68.2	**73.1**	72.5	72.4
TS15	82.6	81.3	82.6	86.3	**87.9**
TS16	76.1	75.5	**76.2**	74.9	70.1
TS17	87.3	83.2	87.4	**94.7**	93.7
TS18	80.0	76.9	80.5	**82.4**	82.2

Table 6
Best accuracy (in percentage) per classifier.

Test subject	Parzen	k-means1	k-means2	ocSVM1	ocSVM2
TS1	99.3	99.3	99.3	**99.5**	99.4
TS2	99.2	99.2	99.2	99.3	**99.4**
TS3	99.3	99.3	99.3	**99.5**	**99.5**
TS4	99.1	99.1	99.1	**99.2**	**99.2**
TS5	98.9	98.9	98.9	**99.0**	**99.0**
TS6	99.3	99.3	99.3	**99.4**	**99.4**
TS7	98.7	98.7	98.7	**98.8**	**98.8**
TS8	99.3	99.3	99.3	**99.4**	**99.4**
TS9	**99.4**	**99.4**	**99.4**	**99.4**	**99.4**
TS10	98.7	98.7	98.7	**98.9**	98.8
TS11	**99.4**	**99.4**	**99.4**	**99.4**	**99.4**
TS12	98.9	98.9	98.9	**99.0**	**99.0**
TS13	99.5	99.5	99.5	**99.6**	**99.6**
TS14	97.1	97.2	97.1	97.3	**97.4**
TS15	98.8	98.8	98.8	**98.9**	**98.9**
TS16	99.2	99.2	99.2	**99.4**	**99.4**
TS17	97.1	97.1	97.1	**97.9**	**97.9**
TS18	98.8	98.8	98.8	**99.0**	**99.0**

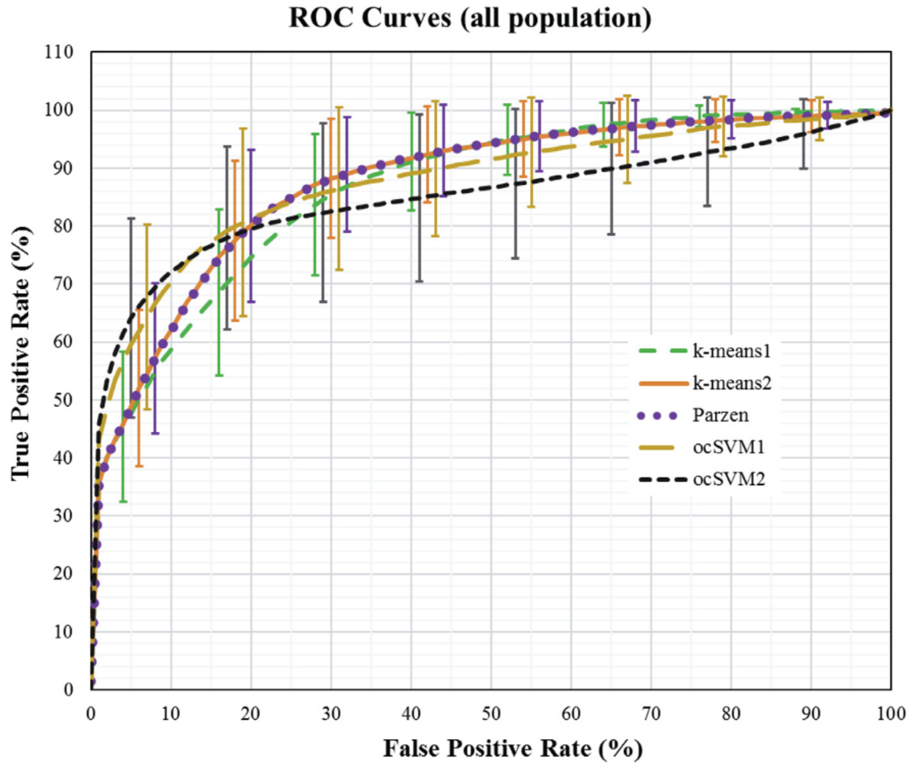

Fig. 2. ROC curves built from mean and standard deviation of all users.

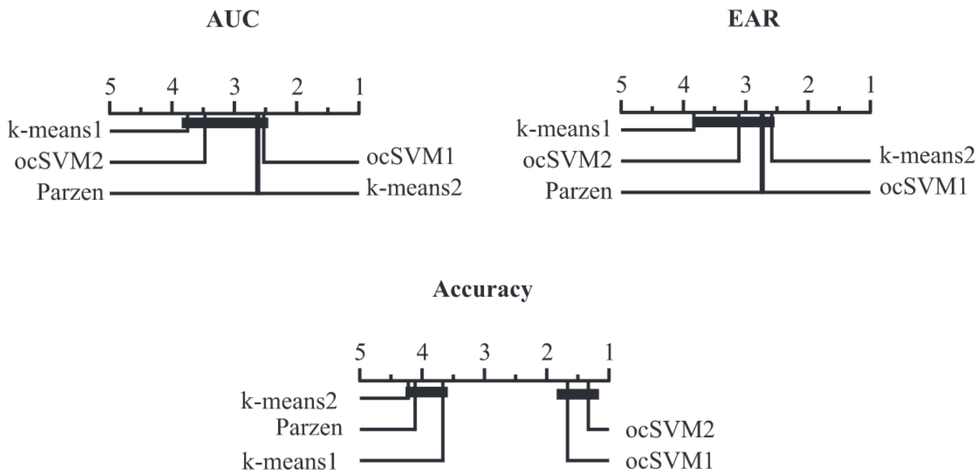

Fig. 3. CD diagrams with the statistical comparisons of SVM, Parzen, k-means1, and k-means2.

These results show that there is plenty of room for improvement. Due to the large amount of data that is generated per user, we plan to further investigate the suitability of Deep Learning approaches [42,43] for discovering patterns that best describe the users and then improve the classification process.

6. Conclusions and further work

Our working hypothesis states that a risk-prone situation induces sudden and significant deviations in standard physiological and behavioural user patterns; thus, potential threat situations can be automatically identified.

In this study, we introduced PRIDE (**P**ersonal **RI**sk **DE**tection), a publicly available dataset that provides a baseline for the development and the fair comparison of personal risk detection mechanisms. PRIDE includes partial information about user behavioural and physiological patterns. Data from test subjects was collected while they carried out ordinary daily life activities, and also under stress scenarios, thereby simulating a dangerous or abnormal condition.

Next, we showed how to use PRIDE to develop a personal risk detection mechanism and found encouraging results: we run several experiments that support our hypothesis that abnormal behaviour can be automatically detected using a one-class classification approach. To achieve our objective, we trained several classifiers based only on the daily behaviour of users; then we tested their accuracy to detect anomalies that we did not include in the training process.

One-class Support Vector Machines achieved the best performance and best average ranking among the tested classifiers for most of the users. However, there is still room for improvement. Owing to the large amount of data that is generated per test subject, we plan to further investigate the suitability of Deep Learning approaches [42,43] to discover patterns that best describe a user aiming at improving the classification process.

Acknowledgements

We thank the members of the GIEE-ML group at Tecnologico de Monterrey for providing invaluable, useful suggestions and advice on earlier versions of this paper. The first author was supported by CONACYT student scholarship 515676. Special thanks to all volunteers for the data collection process, from which PRIDE was built and because of this effort, the dataset is now available to the research community. In addition, we sincerely appreciate Microsoft for their support and donation of wearable sensors.

Annex 1. The PRIDE dataset. $\overline{X}$ and s of all test subject features.

Table 7
Normal conditions dataset. Part I.

	No. of records	Gyroscope accelerometer			Gyroscope angular velocity		
		X axis $\bar{x}$ (s)	Y axis $\bar{x}$ (s)	Z axis $\bar{x}$ (s)	X axis $\bar{x}$ (s)	Y axis $\bar{x}$ (s)	Z axis $\bar{x}$ (s)
TS 1	466,175	−0.066 (0.479)	0.282 (0.491)	0.312 (0.573)	0.346 (13.712)	−0.644 (9.379)	−0.894 (12.138)
TS 2	314,975	−0.060 (0.493)	−0.349 (0.531)	−0.201 (0.551)	−0.646 (20.150)	0.837 (15.469)	−0.090 (16.640)
TS 3	341,645	−0.079 (0.439)	−0.296 (0.452)	0.493 (0.508)	−0.298 (18.403)	−0.120 (12.021)	0.053 (15.084)
TS 4	373,019	0.051 (0.567)	−0.347 (0.424)	0.359 (0.483)	−0.702 (16.034)	−0.411 (11.139)	0.174 (12.828)
TS 5	296,270	−0.094 (0.487)	0.321 (0.473)	0.381 (0.520)	−0.711 (18.799)	0.463 (12.088)	−0.398 (14.399)
TS 6	328,976	−0.214 (0.432)	0.359 (0.435)	0.463 (0.488)	−0.606 (14.530)	−0.431 (9.046)	−0.062 (11.104)
TS 7	288,386	0.024 (0.519)	−0.398 (0.448)	0.318 (0.512)	−0.083 (19.638)	−0.254 (13.010)	−0.945 (16.512)
TS 8	397,320	−0.128 (0.543)	0.263 (0.492)	0.387 (0.471)	−0.412 (14.073)	−0.157 (8.302)	−0.023 (9.557)
TS 9	336,474	−0.190 (0.511)	−0.267 (0.563)	−0.149 (0.541)	0.377 (12.486)	−0.671 (10.083)	−0.879 (10.745)
TS 10	251,383	−0.123 (0.493)	0.334 (0.424)	0.566 (0.360)	−0.344 (13.887)	−0.079 (9.187)	−0.036 (13.403)
TS 11	442,304	−0.032 (0.412)	−0.299 (0.491)	−0.262 (0.640)	−0.601 (15.472)	−0.287 (10.329)	0.058 (11.972)
TS 12	243,701	0.016 (0.485)	0.265 (0.432)	0.520 (0.474)	−0.735 (19.527)	0.087 (12.183)	−0.373 (14.832)
TS 13	431,496	0.019 (0.451)	−0.321 (0.534)	0.225 (0.598)	−0.515 (15.429)	−0.253 (10.246)	0.018 (11.710)
TS 14	160,975	−0.082 (0.498)	0.430 (0.373)	−0.276 (0.582)	0.262 (24.231)	−0.861 (15.893)	−1.255 (19.733)
TS 15	302,863	−0.178 (0.448)	0.287 (0.540)	0.220 (0.588)	−0.722 (19.533)	−0.382 (14.578)	0.030 (15.678)
TS 16	327,804	0.001 (0.481)	0.379 (0.430)	−0.503 (0.428)	−0.832 (18.842)	−0.017 (13.758)	−0.002 (16.473)
TS 17	133,795	−0.094 (0.396)	0.168 (0.628)	−0.356 (0.536)	0.259 (11.996)	−0.627 (7.500)	−0.948 (9.317)
TS 18	335,424	−0.021 (0.511)	−0.376 (0.492)	−0.225 (0.546)	−0.725 (12.759)	0.548 (8.500)	−0.170 (11.065)

Table 8
Normal conditions dataset. Part II.

	Accelerometer			Heart rate	Skin temperature	Pace
	X axis $\bar{x}$ (s)	Y axis $\bar{x}$ (s)	Z axis $\bar{x}$ (s)	$\bar{x}$ (s)	$\bar{x}$ (s)	$\bar{x}$ (s)
TS 1	−0.066 (0.479)	0.282 (0.491)	0.312 (0.573)	71.856 (10.254)	33.553 (1.300)	47.613 (249.390)
TS 2	−0.059 (0.493)	−0.349 (0.531)	−0.201 (0.551)	64.426 (10.274)	32.821 (1.412)	134.718 (431.197)
TS 3	−0.079 (0.439)	−0.296 (0.452)	0.493 (0.508)	71.488 (8.425)	31.885 (1.789)	74.004 (319.042)
TS 4	0.051 (0.567)	−0.347 (0.424)	0.359 (0.483)	68.335 (10.309)	32.127 (2.239)	49.351 (271.310)
TS 5	−0.094 (0.487)	0.321 (0.473)	0.381 (0.520)	68.911 (9.593)	33.381 (2.001)	65.316 (301.010)
TS 6	−0.214 (0.432)	0.359 (0.435)	0.463 (0.488)	66.160 (11.398)	32.749 (1.144)	49.332 (248.829)
TS 7	0.024 (0.519)	−0.398 (0.447)	0.318 (0.512)	74.341 (9.454)	33.184 (3.004)	156.612 (438.505)
TS 8	−0.128 (0.543)	0.263 (0.491)	0.387 (0.471)	65.663 (11.600)	31.970 (1.880)	43.232 (219.687)
TS 9	−0.190 (0.511)	−0.267 (0.563)	−0.149 (0.541)	81.414 (11.777)	34.166 (1.571)	46.143 (247.978)
TS 10	−0.123 (0.493)	0.334 (0.424)	0.566 (0.360)	77.573 (14.253)	32.970 (1.239)	40.556 (220.579)
TS 11	−0.032 (0.412)	−0.299 (0.492)	−0.262 (0.640)	72.384 (10.791)	34.237 (1.426)	40.066 (232.637)
TS 12	0.016 (0.485)	0.265 (0.432)	0.520 (0.474)	71.344 (9.123)	38.917 (1.942)	65.041 (296.546)
TS 13	0.019 (0.451)	−0.321 (0.534)	0.225 (0.598)	71.832 (15.471)	31.981 (2.379)	72.149 (296.384)
TS 14	−0.082 (0.498)	0.430 (0.373)	−0.276 (0.582)	70.741 (7.681)	32.512 (1.615)	102.405 (375.538)
TS 15	−0.178 (0.448)	0.287 (0.540)	0.220 (0.588)	71.081 (8.969)	32.926 (2.354)	80.668 (340.809)
TS 16	0.001 (0.481)	0.379 (0.430)	−0.503 (0.428)	73.199 (10.221)	33.224 (2.119)	84.804 (339.817)
TS 17	−0.094 (0.396)	0.168 (0.628)	−0.356 (0.536)	61.294 (11.812)	34.141 (1.331)	70.054 (325.963)
TS 18	−0.021 (0.511)	−0.376 (0.492)	−0.225 (0.546)	73.254 (10.305)	41.339 (1.881)	69.961 (284.993)

Table 9
Normal conditions dataset. Part III.

	Speed $\bar{x}$ (s)	UV $\bar{x}$ (s)	Δ Pedometer $\bar{x}$ (s)	Δ Distance $\bar{x}$ (s)	Δ Calories $\bar{x}$ (s)
TS 1	4.992 (23.964)	0.022 (0.148)	0.068 (0.513)	5.277 (40.239)	0.026 (0.810)
TS 2	11.247 (33.578)	0.020 (0.183)	0.180 (5.749)	14.001 (449.963)	0.037 (1.902)
TS 3	7.146 (28.243)	0.036 (0.203)	0.107 (2.468)	8.187 (183.953)	0.034 (1.975)
TS 4	3.871 (19.806)	0.035 (0.184)	0.087 (8.173)	6.946 (653.910)	0.030 (1.789)
TS 5	5.678 (24.098)	0.038 (0.203)	0.111 (6.601)	8.859 (527.082)	0.037 (1.954)
TS 6	5.123 (23.836)	0.020 (0.138)	0.087 (3.533)	6.788 (308.571)	0.037 (2.059)
TS 7	17.295 (46.119)	0.034 (0.206)	0.298 (26.685)	24.777 (2186.446)	0.042 (1.936)
TS 8	5.117 (24.167)	0.040 (0.195)	0.088 (4.579)	6.993 (362.702)	0.034 (1.597)
TS 9	4.311 (21.449)	0.027 (0.173)	0.068 (1.205)	4.804 (85.353)	0.022 (0.797)
TS 10	5.343 (26.415)	0.025 (0.156)	0.101 (6.972)	7.950 (550.756)	0.046 (3.286)
TS 11	3.477 (18.744)	0.000 (0.000)	0.057 (0.659)	3.841 (43.986)	0.024 (0.807)
TS 12	5.966 (25.317)	0.046 (0.226)	0.105 (5.378)	8.240 (417.039)	0.040 (2.834)
TS 13	9.248 (35.681)	0.056 (0.268)	0.253 (80.693)	11.237 (463.311)	0.042 (1.507)
TS 14	8.549 (29.013)	0.039 (0.193)	0.320 (31.097)	19.210 (1361.480)	0.055 (4.229)
TS 15	6.909 (27.264)	0.022 (0.183)	0.198 (12.125)	15.908 (970.020)	0.044 (1.611)
TS 16	7.687 (28.507)	0.011 (0.105)	0.929 (469.171)	8.790 (208.055)	0.035 (1.633)
TS 17	5.485 (23.726)	0.004 (0.060)	0.282 (31.805)	22.152 (2507.279)	0.062 (5.433)
TS 18	8.582 (31.890)	0.001 (0.029)	0.120 (2.264)	9.411 (177.234)	0.035 (2.723)

Table 10
Abnormal conditions dataset. Part I.

	No. of records	Gyroscope accelerometer			Gyroscope angular velocity		
		X axis $\bar{x}$ (s)	Y axis $\bar{x}$ (s)	Z axis $\bar{x}$ (s)	X axis $\bar{x}$ (s)	Y axis $\bar{x}$ (s)	Z axis $\bar{x}$ (s)
TS 1	770	0.113 (0.619)	−0.679 (0.414)	0.017 (0.417)	−0.846 (40.900)	−1.102 (38.233)	0.524 (33.024)
TS 2	608	0.384 (0.501)	−0.699 (0.492)	0.114 (0.642)	2.209 (50.987)	2.188 (31.660)	−3.077 (35.142)
TS 3	494	0.339 (0.803)	−0.655 (0.673)	0.374 (0.410)	−12.002 (59.791)	−4.086 (32.065)	2.214 (33.438)
TS 4	708	0.431 (0.609)	−0.346 (0.387)	0.324 (0.489)	−3.294 (42.243)	−2.153 (34.449)	0.413 (33.770)
TS 5	792	0.586 (0.783)	0.532 (0.525)	0.161 (0.349)	2.098 (29.158)	−2.664 (27.008)	-0.408 (38.388)
TS 6	674	0.457 (0.669)	0.571 (0.658)	0.560 (0.446)	1.093 (47.790)	−1.054 (32.493)	0.516 (40.079)
TS 7	770	0.411 (0.685)	−0.635 (0.606)	0.298 (0.389)	1.095 (41.332)	1.919 (35.214)	−2.004 (42.678)
TS 8	724	0.580 (0.838)	0.832 (0.657)	−0.214 (0.617)	2.072 (39.552)	−10.207 (39.374)	−1.571 (36.128)
TS 9	566	0.086 (0.647)	−0.399 (0.556)	0.449 (0.350)	2.317 (40.801)	−0.828 (36.996)	−5.515 (42.064)
TS 10	767	0.299 (0.517)	0.321 (0.818)	−0.023 (0.532)	2.590 (37.810)	1.085 (25.954)	−0.927 (30.640)
TS 11	647	0.365 (0.739)	−0.236 (0.626)	0.231 (0.575)	−2.795 (45.353)	5.866 (32.214)	3.660 (49.090)
TS 12	679	0.740 (0.716)	0.058 (0.600)	0.454 (0.466)	−0.114 (41.168)	−1.030 (35.996)	−2.367 (36.503)
TS 13	485	0.491 (0.826)	−0.549 (0.526)	0.030 (0.494)	−0.647 (41.101)	−4.246 (41.316)	2.940 (41.405)
TS 14	1066	0.464 (0.656)	0.491 (0.502)	0.108 (0.507)	−5.939 (40.240)	5.508 (32.998)	−1.785 (33.435)
TS 15	881	0.245 (0.593)	0.799 (0.687)	−0.095 (0.430)	7.482 (48.483)	2.926 (37.574)	−0.901 (43.749)
TS 16	578	0.560 (0.796)	0.809 (0.667)	−0.130 (0.475)	−7.245 (39.853)	7.422 (31.144)	0.075 (37.856)
TS 17	941	0.194 (0.525)	0.689 (0.534)	0.295 (0.501)	1.151 (45.200)	0.685 (25.359)	−0.138 (29.349)
TS 18	904	0.320 (0.574)	−0.656 (0.339)	0.213 (0.428)	−0.638 (38.582)	2.106 (27.732)	−3.557 (33.302)

Table 11
Abnormal conditions dataset. Part II.

	Accelerometer			Heart rate	Skin temperature	Pace
	X axis $\bar{x}$ (s)	Y axis $\bar{x}$ (s)	Z axis $\bar{x}$ (s)	$\bar{x}$ (s)	$\bar{x}$ (s)	$\bar{x}$ (s)
TS 1	0.110 (0.622)	−0.680 (0.411)	0.015 (0.417)	97.097 (22.148)	31.739 (0.429)	258.291 (371.325)
TS 2	0.395 (0.482)	−0.696 (0.511)	0.156 (0.670)	80.655 (6.793)	29.113 (1.196)	460.569 (419.805)
TS 3	0.338 (0.805)	−0.655 (0.667)	0.374 (0.411)	87.263 (17.918)	28.942 (1.791)	287.767 (418.495)
TS 4	0.431 (0.611)	−0.346 (0.388)	0.324 (0.491)	82.602 (15.916)	28.941 (1.645)	558.905 (633.728)
TS 5	0.603 (0.781)	0.538 (0.528)	0.154 (0.352)	81.412 (11.368)	33.933 (0.829)	339.201 (542.872)
TS 6	0.457 (0.668)	0.569 (0.652)	0.555 (0.450)	85.220 (14.215)	29.616 (0.402)	246.426 (371.220)
TS 7	0.412 (0.685)	−0.635 (0.605)	0.297 (0.390)	76.544 (6.768)	29.921 (1.307)	393.745 (574.313)
TS 8	0.579 (0.837)	0.818 (0.653)	−0.215 (0.615)	79.148 (8.492)	28.358 (0.921)	221.006 (310.291)
TS 9	0.085 (0.643)	−0.399 (0.555)	0.448 (0.347)	79.936 (12.531)	30.151 (1.243)	160.900 (259.476)
TS 10	0.298 (0.518)	0.321 (0.817)	−0.023 (0.532)	81.675 (11.959)	30.589 (1.417)	221.785 (413.279)
TS 11	0.365 (0.739)	−0.236 (0.625)	0.232 (0.573)	86.611 (20.806)	31.249 (1.198)	206.471 (305.513)
TS 12	0.746 (0.740)	0.054 (0.607)	0.446 (0.482)	79.031 (8.765)	39.856 (1.977)	262.915 (472.168)
TS 13	0.492 (0.829)	−0.550 (0.528)	0.030 (0.493)	79.563 (8.671)	31.597 (0.993)	230.324 (435.552)
TS 14	0.466 (0.661)	0.490 (0.494)	0.102 (0.501)	83.398 (14.065)	31.157 (0.984)	251.290 (415.069)
TS 15	0.253 (0.597)	0.799 (0.673)	−0.085 (0.433)	79.748 (11.037)	27.039 (0.673)	330.247 (538.912)
TS 16	0.564 (0.799)	0.811 (0.669)	−0.131 (0.475)	88.540 (20.952)	33.407 (0.918)	216.730 (353.419)
TS 17	0.189 (0.516)	0.690 (0.533)	0.310 (0.499)	81.963 (16.540)	27.289 (0.985)	120.472 (243.084)
TS 18	0.320 (0.573)	−0.655 (0.342)	0.213 (0.428)	93.290 (24.697)	37.815 (2.559)	183.941 (356.975)

Table 12
Abnormal conditions dataset. Part III.

	Speed $\bar{x}$ (s)	UV $\bar{x}$ (s)	Δ Pedometer $\bar{x}$ (s)	Δ Distance $\bar{x}$ (s)	Δ Calories $\bar{x}$ (s)
TS 1	118.190 (133.248)	0.118 (0.323)	1.164 (1.662)	123.790 (178.250)	0.078 (0.268)
TS 2	176.948 (122.629)	0.523 (0.500)	1.714 (1.680)	176.194 (181.270)	0.094 (0.292)
TS 3	134.763 (160.947)	0.223 (0.516)	1.279 (1.846)	142.591 (229.427)	0.071 (0.257)
TS 4	77.801 (92.240)	0.097 (0.297)	0.893 (1.601)	82.054 (159.729)	0.055 (0.228)
TS 5	104.194 (138.165)	0.665 (0.472)	0.990 (1.782)	105.869 (190.114)	0.037 (0.188)
TS 6	144.616 (157.949)	0.405 (0.491)	1.315 (1.788)	151.721 (210.877)	0.042 (0.200)
TS 7	116.610 (145.402)	0.553 (0.832)	1.047 (1.710)	121.081 (203.444)	0.032 (0.177)
TS 8	140.436 (158.209)	0.394 (0.489)	1.199 (1.776)	141.738 (221.937)	0.033 (0.179)
TS 9	117.992 (149.526)	0.498 (0.500)	1.155 (1.712)	127.212 (193.314)	0.023 (0.150)
TS 10	85.001 (126.758)	0.248 (0.432)	0.866 (1.616)	95.557 (180.922)	0.031 (0.174)
TS 11	85.121 (115.315)	0.233 (0.423)	0.989 (1.573)	94.414 (152.147)	0.039 (0.193)
TS 12	124.980 (162.112)	0.236 (0.492)	1.037 (1.939)	125.973 (235.163)	0.037 (0.188)
TS 13	121.590 (164.312)	0.243 (0.598)	1.010 (1.775)	128.878 (238.527)	0.035 (0.184)
TS 14	88.249 (126.044)	0.067 (0.249)	0.797 (1.455)	86.081 (170.038)	0.034 (0.181)
TS 15	109.222 (152.789)	0.314 (0.465)	0.981 (1.711)	114.547 (205.342)	0.034 (0.181)
TS 16	139.817 (169.673)	0.351 (0.478)	1.128 (1.678)	141.412 (222.837)	0.059 (0.235)
TS 17	71.153 (125.804)	0.000 (0.000)	0.618 (1.416)	72.259 (169.026)	0.052 (0.222)
TS 18	85.978 (125.400)	0.198 (0.399)	0.772 (1.468)	86.354 (168.715)	0.063 (0.243)

Supplementary materials

Supplementary data associated with this article can be found, in the online version, at 10.1016/j.ins.2016.08.006.

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