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MOBILE & WIRELESS HEALTH

Development of a Strategy to Predict and Detect Falls Using Wearable Sensors

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Abstract

Falls are a prevalent problem in actual society. Some falls result in injuries and the cost associated with their treatment is high. This is a complex problem that requires several steps in order to be tackled. Firstly, it is crucial to develop strategies that recognize the locomotion mode, indicating the state of the subject in various situations. This article aims to develop a strategy capable of identifying normal gait, the pre-fall condition, and the fall situation, based on a wearable system (IMUs-based). This system was used to collect data from healthy subjects that mimicked falls. The strategy consists, essentially, in the construction and use of classifiers as tools for recognizing the locomotion modes. Two approaches were explored. Associative Skill Memories (ASMs) based classifier and a Convolutional Neural Network (CNN) classifier based on deep learning. Finally, these classifiers were compared, providing for a tool with a good accuracy in recognizing the locomotion modes. Results have shown that the accuracy of the classifiers was quite acceptable. The CNN presented the best results with 92.71% of accuracy considering the pre-fall step different from normal steps, and 100% when not considering.

Keywords Inertial Measurement Units (IMUs) · Gait analysis · Principal Component Analysis (PCA) · Associative Skill Memories (ASMs) · Convolutional Neural Network (CNN) · Deep learning

Introduction

Background and motivation

Human walking, which is one of many types of human gait, can be considered a complex and a common human physical activity that can be performed in a variety of ways and directions, and that requires muscular strength, joint's mobility and coordination of the central nervous system [1]. According to several studies [2–6], normal gait can be affected by a number of neurological pathologies, e.g. Parkinson's Disease (PD), Multiple Sclerosis (MS), Alzheimer's Disease (AD) or Gaucher's Disease (GD).

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PD has direct repercussions on the patient's gait since it affects the attention, language, memory, and visuospatial functions [3, 7]. Events such as Freezing of Gait (FOG), shuffling gait and festination are usually found in patients with PD and they are related to the step length. FOG happens when the patient has difficulty starting walking; shuffling gait when the patient drags the feet during walking; and festination is characterized by quick and short strides [8]. Further, Amboni et al. [3] concluded that step length is an independent predictor of dysfunction in PD when on medication and during a cognitive task.

MS, an autoimmune disease of the central nervous system, causes fatigue, spasticity and abnormal coordination, which contributes to gait dysfunction [9]. Liparoti et al. [4] compared patients with Relapsing-Remitting Multiple Sclerosis (pwRR-MS) and healthy subjects during walking (single task), and cognitive dual tasks (CogDT). During walking, pwRR-MS presented a higher cycle time, in terms of velocity, higher stance time, swing time, and coefficients of variability of swing time, considering stability, and a higher ankle dorsiflexion, regarding kinematic parameters, when compared to healthy subjects. During CogDT, the changes of velocity and stability parameters were similar to the single task, and they also observed an increase of the double limb support.

One of the most common forms of degenerative dementia, AD, has been described mainly by the occurrence of cortical atrophy, which determines memory deficits, compromises executive function and leads to changes in personality and behaviour, or even, to language disturbances [10]. Rucco et al. [5] studied the gait pattern of patients with AD and Frontotemporal Dementia (bvFTD) in single (motor) and dual task (motor and cognitive) conditions to test if specific gait patterns are induced by either frontal or temporal degeneration. During single task, the bvFTD group was slower (parameters: speed, stride length, cycle time and cadence) and more unstable (parameters: double limb support time, double/single limb support time ratio, and stance time) when compared to healthy subjects, while AD only presented two compromised stability parameters, namely the double limb support time and the double/single limb support time ratio. During motor dual task, both groups presented an overall deterioration. In the bvFTD group was observed an impairment of velocity and stability parameters. The AD group presented a significantly deterioration with more indices of velocity (cycle time and cadence) and most of stability parameters.

GD is classified in three different types and is caused by a defective activity of the enzyme beta-glucocerebrosidase (GBA) that affects the nervous system, mainly on GD-type 2 and 3 [11]. Sorrentino et al. [6] analyzed spatiotemporal and kinematic parameters of gait between patients with GD and healthy subjects. Their purpose was to test if motion analysis could help to define the possible motor impairment in GD-type 1 patients. The authors found kinematic parameters, namely segments of ankle, knee and thigh angles, that are statistically significantly lower in GD-type 1 patients.

As it has been shown above, gait evaluation and assessment usually look for abnormalities caused by these pathologies. Thus, an early diagnosis will contribute to the decision of the treatment that should be chosen [12]. Additionally, it can help to prevent the occurrence of falls, which is one of the most common health concerns especially in elderly people. This alarming incident is critical not only in terms of the number of events, but also in the consequent reduction in the quality of life, as well as in terms of health costs [13, 14]. Moreover, an increase in the number of falls and related injuries is expected since the most of health problems affect the elderly [15] and the average life expectancy is increasing in developed countries [16]. Only in the United States of America (USA), \$19 billion were spent on the direct medical costs of fall-related injuries in 2000 [13]. In 2015, this has risen to more than \$31 billion in the Medicare [17], and by 2020 expenses linked to fall-related injuries to senior citizens are expected to cost roughly \$43.8 billion [18].

This demands a detailed knowledge about gait's characteristics as well as their monitoring and evaluation over time. On the other hand, the use of medication of even normal physiological variations can exhibit the same gait variations as the mentioned and may result in alterations of balance, being as well risks of fall. In order to decrease the incidence of fall and healthcare costs associated with fall-related injuries, it is necessary to widely implement fall prevention methods. Currently, there are procedures to evaluate the patient's risk of fall, where some parameters are assessed and then preventive measures such as medication or diet are implemented according to the determined level of risk. There are also real-time monitoring devices capable of detecting falls [19, 20]. Some of them are also able to act in order to avoid the subject's impact on the floor [21].

Problem statement and scope

In this article, it was decided to use an existing IMU-based system [22, 23], which is wearable, wireless, and capable of collecting data from human gait. This information is important to obtain related gait parameters or metrics [24]. Furthermore, statistical analysis through Principal Component Analysis (PCA) is applied to reduce the number of metrics. These selected metrics are used, posteriorly, in an offline strategy to identify different locomotion modes, especially normal gait, the pre-fall's condition, and the fall. To do so, basic familiarity with human locomotion, as well as knowledge of sensor characteristics and placement, specification of walking trials, and the most relevant gait parameters to this particular situation are required. Additionally, it is important to understand the evolution of the gait's parameters during the gait cycle and the way the fall and pre-fall's situations influence these gait parameters. Finally, two strategies are applied to identify the locomotion modes. A simple statistical classifier built through Associative Skill Memories (ASMs) combined with simple z-tests, and a deep learning based Convolution Neural Network (CNN). Results will be compared based on the accuracy of both classifiers.

Study importance and objective

Scientific literature concerning falls is highly focused on fall detection systems and fall risk assessment tools [25, 26]. Fall detection systems are often based on impact detection [27–29]. However, other solutions achieved better accuracy results namely: decision tree classifiers [30], fuzzy logic [28], and use of machine learning algorithms [31], with up to 97% success rate. On the other hand, clinical fall risk assessment tools apply measures such as medication or physical exercise in order to reduce the risk of fall [32]. Rucco et al. [26] identified the main trends related to wearable sensor's typology and location, and tasks for monitoring falls with different purposes: fall risk assessment, fall detection and fall prevention. Their analysis revealed that most of the considered methodologies uses two sensors at maximum, and accelerometers and gyroscopes are the most widespread technologies. Considering the position of the sensors, the trunk is the most used segment due to the crucial role in static and dynamic stability. With regards to the task standpoint, in case of static stability assessment, usually a standing test with open or closed eyes is performed. On the other hand, for dynamic evaluations, a walking task or a sit-to-stand test are frequently used in order to detect postural variations.

Recently, some authors focused on detecting a fall before it happens in humans and robots [21, 33, 34]. However, these are highly focused in threshold based algorithms, and therefore very subject dependent. Besides up to our knowledge there is still no such framework proposed regarding biped locomotion in humans using IMUs. Hence we consider necessary to establish a framework that takes advantage of perceptual information to monitor movement execution in real time, and use it to prevent undesirable situations such as falls. Subsequently, this work's goal is to develop an offline classifier capable of distinguish normal gait from fall and pre-fall's situations, through the use of relevant gait's parameters by means of an IMU-based system during some daily life activities. As future work, it is pretended the implementation of one or more classifiers in real-time to identify fall and pre-fall situations.

The remainder of this paper is organized as follows. In Section "Methods and materials" the methods and materials are adopted. Thus, it is described the IMU-based system used by the authors. Also, the metrics and the method to select the most relevant ones are presented. The implemented classifiers, statistical classifier and CNN, are described as well as the methodology, and the evaluation of classification performance. Sections "Stage 1", "Stage 2", and "Stage 3" provide information about stages of the methodology. Results are presented in Section "Results". Section "Discussion" contains the discussions. Conclusions and future work are in Section "Conclusion".

Methods and materials

Problem overview

As described in Fig. 1, sensors' raw data were collected from trials, and these data were synchronized in time, interpolated in case of loss of samples, and normalized through a normalization process. Subsequently, each normalized gait cycle/motion period was extracted from data through a step detector algorithm presented in [35], which needs an IMU on the upper foot and it is capable of determining stance and swing phases. These normalized sensor data are phase-indexed, which eliminates issues with the rhythmicity of locomotion. Further, this phase-indexation is very important since it removes the need for temporal indexation to recognize locomotion as discussed in [34]. For each gait cycle, the metrics presented in Section 2 were calculated. Gait metrics are truly important to characterize human locomotion.

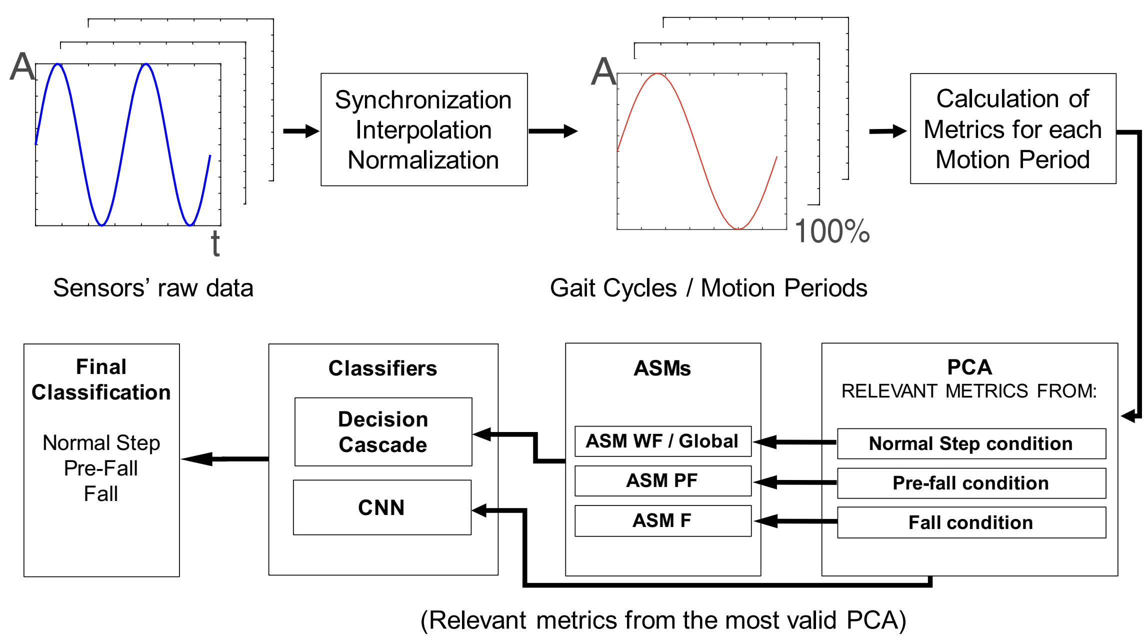

Fig. 1 Block diagram of the problem overview

However, due to their quantity, a preliminary study based on PCA was important to determine which features are relevant to characterize the human gait and to be used on the construction of the classifiers.

From here on, development is divided in three different **Stages**, since in order to identify fall/risk situations, two different classifiers were implemented based on data from IMUs attached to body segments. In Stage 1, ASMs were constructed to be used in the decision cascade, which is a statistical classifier. In Stage 2, a CNN was also used to classify different locomotion modes. Different from the statistical classifier, the CNN just needs a single PCA. So, relevant metrics from the most statistically valid PCA were chosen to train the neural network. Both classifiers were tested. Finally, a new set of small indoor trials was performed in order to verify the implemented classifiers in a different and more complex scenario - Stage 3.

Magnetic/inertial-based measurement system

The overall system, able to monitor human gait, is shown in Fig. 2. A personal computer, a SmartRF05EB (base station), and sensory modules are the three main elements of the used system [22, 23]. A MPU-6000 [36] from InvenSense, which contains a three-axis MEMS Accelerometer (Acc), a Gyroscope (Gyr), and a temperature sensor, allowed an integration with a Honeywell three-axis Digital Compass IC HMC5883L (Mag) [37]. This sensor board is connected to the CC2530EM module from Texas Instruments, which is a System-on-chip solution to IEEE 802.15.4 applications (IEEE Std 802.15.4, 2006), through two 20-pin header connectors. Thus, a sensory module is formed. Throughout the project, MPU-6000 was programmed to have a Full-Scale Range of ±8g for Acc, ±1000°/s for Gyr, and ±0.88 Gauss for Mag.

The CC2530EM module is also present in the SmartRF05EB. This module is used to establish communication between sensory modules and base station SmartRF05EB via wireless. Data received by the base station is routed to the Personal Computer via serial port. Subsequently, data are properly processed. Each sensory module can be firmly attached to one body segment, and it is calibrated before each gait monitoring. The entire system is controlled by a Graphical User Interface (GUI) [22]. The sampling frequency is at least 0.63Hz, and 160Hz is the maximum value. However, 30Hz is the minimum value used to monitor human gait in this project. An amount of five IMUs were used attached to the lower back, to both back thighs, and to both feet. Figure 3 depicts the attachment location of the IMUs. IMUs were calibrated prior to trials similarly to [38].

Gait metrics

From all available metrics in the scientific literature, only the following metrics were selected, namely: i) Roll, Pitch and Yaw angles [29]; ii) Gait events (GE or gait phases) [39]; iii) Hip joint angles (Joint_Ang – Left and Right) [29, 39]; iv) Approximate Entropy (AE) from all sensors [39]; v) Activity Signal Magnitude Area (ASMA - from all Acc axes) [29]; vi) Signal Vector Magnitude (SVM - from all Acc axes) [29]; vii) dSVM/dt [29]; viii) SVd (Dynamic Sum Vector) [27]; ix) Vertical acceleration (Z2_Vert_Acc)[27]; x) Signal Magnitude Area (SMA- from all Acc axes) and

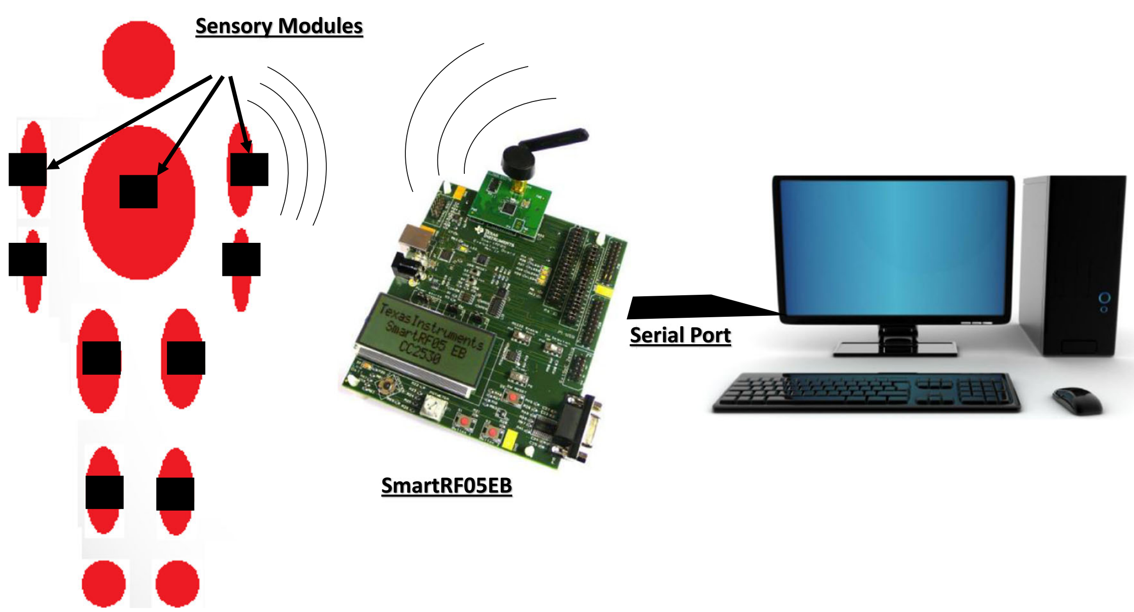

Fig. 2 Magnetic/inertial measurement system elements

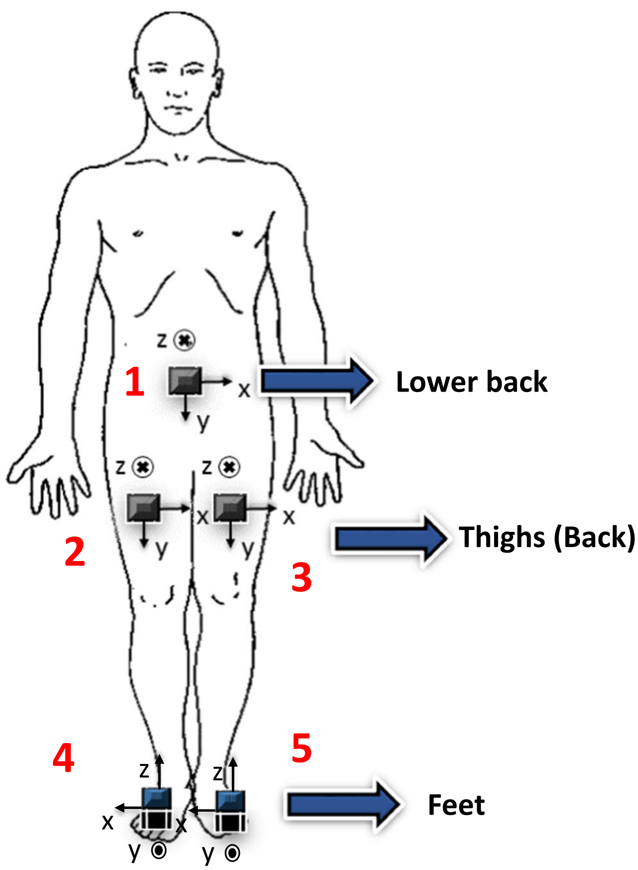

Fig. 3 Attachment location of the used IMUs for the trials (Dark IMUs are in the back of the body; Numbers represent the physical addresses of the IMUs)

its derivate [29]; xi) Fast Fourier Transform (FFT) from all sensors' axes [39]; and xii) Wavelet decomposition (WD) also from all sensors' axes [40]. Besides, raw data from the sensors were also included. Thus, a total of 228 signals are calculated per trial or gait cycle. From now on the term metric or variable will be used to mention these signals.

The aforementioned metrics were selected because most of them can be calculated in real-time, and they vary on an instant basis as opposed to periodic metrics like step lenght or cadence that only have one value per gait cycle. So, we decided to only use metrics that are described by signals.

Finally, due to the great amount of metrics, it is necessary the use of a nomenclature to better understand what metrics are being used in the context. Concerning the raw data from the sensors, the nomenclature used is "Sensor_Axis_PhysicalAddress". For example, Mag_X_3 means "Mag X-axis from the sensory module number 3". On the other hand, metrics derived from more than one sensor need a different nomenclature: "DerivedMetric_Sensor_Axis_PhysicalAddress". For example, AE_Mag_X_3 means "Approximate Entropy from the Mag X-axis of the sensory module number 3".

Principal Component Analysis (PCA)

PCA is able to reduce the dimensionality of a data set consisting of a large number of interrelated variables [41]. Thus, PCA is a data analysis tool to identify patterns in a data set, and express their similarities and differences. Once these patterns have been found, data can be reduced by obtaining a smaller set of variables. Thus, given a set of correlated variables, PCA uses orthogonal transformations to transform them into fewer uncorrelated variables (major components or principal components - PCs), and which are ordered so that the first few retain most of the variation present in all of the original variables [41]. These components are calculated and can be selected in order to minimize the loss of information that the initial variables contain. The principal components are ordered according to the explained variability. Within the scope of the applications of this method, the components that retain most of the variation present in are chosen [42].

In order to perform PCA, the data are separated in gait cycles and organized into a $n \times m \times p$ 3D matrix where each row (n) is an observation, each column (m) is a metric in the sample (p). Usually, in the literature it is necessary to calculate the mean on each dimension of an array with a dataset. However, a PCA is performed for each sample (p) of each metric as depicted in Fig. 4. This process brings more information to the feature selection.

The output of each PCA is a set of p $m \times m$ matrices where the columns represents the PCs, and each row represent a metric. Concerning the PCs, the first column is the most significant one, and the last column is the least significant one. Since it is intended to extract the variables, each element of each output matrix of PCA is squared. Since there are p matrices (PCAs), all squared matrices are summed, and the proportion of each variable is obtained (PC value). Then, the number of relevant PCs are selected according to the Kaiser's rule/criterion [41], where only PCs whose variances exceed 1 are retained (or 10% in case of percentage). Then, a similar proportion of PCs is obtained for each metric, and metrics are selected to be used further if their PC value is greater than $\frac{1}{m}$. This means that variables that explain most of the variability of the data are selected.

Associative Skill Memories (ASMs)

Some tasks/skills can be seen as "stereotypical" movements - performed or executed in a typical repetitive fashion, thus with typical repetitive perceptual information. The association of this prevalent/frequent information ("sensor footprint") with the corresponding movement parametrization (independent of policy/movement representation e.g. DMPs) [43, 44] is known as "Associative Skill Memory" [45]. It is labelled "associative" as the memory derives from

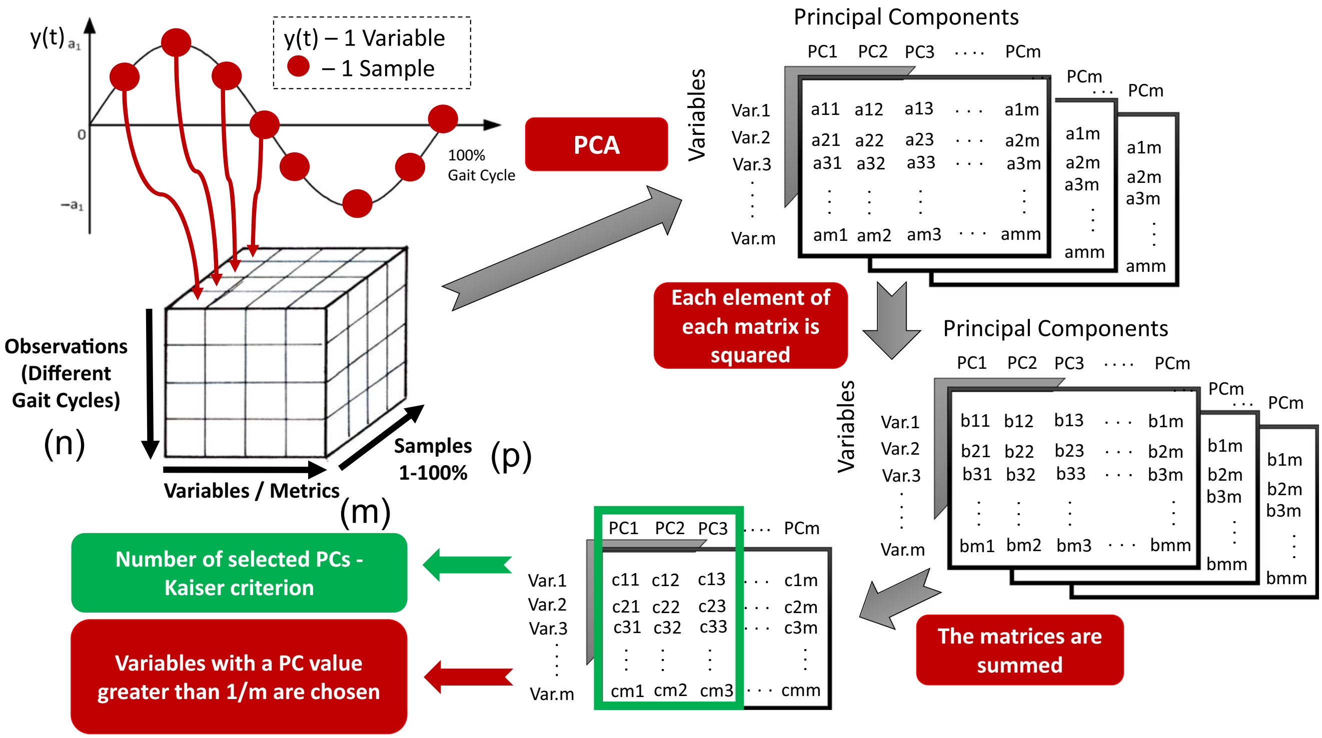

Fig. 4 Set of steps to obtain the most relevant variables

the association of sensor data with the movement (although with the movement parametrization and not from the data itself).

One could choose to store or represent an ASM in a multitude of ways - what it is relevant is the underlying concept and not the mathematical structure. One simple and straightforward way to achieve this is for instance, directly storing time-indexed averaged values of the sensor data $\overline{X}_{ASM}$. As robots and the real world are inherently noisy, there is a particular amount of variability associated with movement execution and sensor data acquisition, and as such storing data standard deviation is also helpful $z\widehat{\sigma}_{ASM}$. This allows to establish a confidence interval associated with a particular movement:

$$X_{trial}(p) > \overline{X}_{ASM}(p) - z\widehat{\sigma}_{ASM}(p) \wedge \\ X_{trial}(p) < \overline{X}_{ASM}(p) + z\widehat{\sigma}_{ASM}(p) \quad (1)$$

where $X_{trial}(p)$ is the variable's data of the current trial p, and z represents a normal quantile which scales the width of the interval. There are several attractive applications of this approach: it allows to indentify possible failure conditions (e.g. fall) whenever incoming perceptual data $X_{trial}(p)$ falls out of this band. Assuming a null hypothesis of "The data is within normal/typical values for this task/movement", then data within the interval entails task conformity. In the aternative case, we can assume there is a high probability of failure occurring, or that movement objective will not be achieved at the end of the trial.

The value of z therefore defines a threshold for conformity, and should be tailored to each specific task. Additionally, due to possibility of occasional/sporadic/erratic values, additional thresholds are specified for perceptual entries (sensors) M and the minimum time interval (N). If the system detects at least M metrics, failing for N instants consecutively, then it is predicted that, based on the previous experiences stored into the ASM, the task will fail. z, M, and N can be determined empirically.

Convolutional Neural Networks (CNNs)

CNNs are tools for deep learning and were inspired on the biological structure of the visual cortex, which contains arrangements of simple and complex cells [46]. A CNN convolves learned features with input data, and uses 2D convolutional layers, making this architecture well suited to processing 2D data, such as images [47–50]. This type of deep neural network eliminates the need for manual feature extraction, which is the big difference between machine learning and deep learning, so it is not necessary to identify features to classify images [49, 51]. In turn, features are extracted directly from images. The relevant features are not pre-trained. They are learned while the network trains on a collection of images instead [47–50]. Thus, deep learning models can be highly accurate, but it requires: i) large amounts of labelled data; and ii) substantial computing power (e.g. high-performance GPUs have a parallel architecture that is efficient for deep learning) [47, 49]. Indeed, deep learning exhibits several attractive characteristics: convergence to a global optimal, avoiding the local minima and over-fitting in the training process; ability to minimize both structural and empirical risk leading to a better generalization for new data classification even with a limited training data set, producing stable and reproducible results; capability of operate with nonlinear and multidimensional data, as parameters of gait [47–50].

As CNN it was used an online available Matlab toolbox supporting 1D, 2D and 3D kernels (*hagaygarty/mdCNN*) [52]. Once each motion period is represented by a matrix, each one is regarded as an image (2D). The default size of each input image is a 28×28 matrix [52], however the size can be modified.

Evaluation of classification performance

In order to evaluate the performance of the statistical classifier in locomotion mode recognition, accuracy, sensitivity and specificity are commonly used. Accuracy, as expressed in Eq. 2, is defined as the classifier's ability to accurately recognize the gait patterns in the classification. TP, FP, TN and FN correspond to true positive, false positive, true negative and false negative values, respectively [53].

$$\text{Accuracy}(\%) = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}} \times 100\% \tag{2}$$

Sensitivity, or True Positive Rate (TPR), presented in Eq. 3, measures the proportion of actual positives which are correctly identified as such. 1-TPR represents the False Negative Rate.

$$\text{Sensitivity}(\%) = \frac{\text{TP}}{\text{TN} + \text{TP}} \times 100\% \tag{3}$$

Specificity (SPC), showed in Eq. 4, measures the proportion of negatives which are correctly identified as such [53]. It is possible to determine the Negative Likelihood Ratio (NLR), a ratio between false and true negatives, through a confusion matrix [54]. 1-SPC represents the False Positive Rate.

$$\text{Specificity}(\%) = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \tag{4}$$

Besides, conclusions about the performance of the failure detection algorithm were based on a Detection Score (DS) computed from sensitivity and specificity values [34]:

$$\text{Detection Score} = \sqrt{\text{sensitivity}^2 + \text{specificity}^2} \tag{5}$$

which can be interpreted as inversely proportional to the distance to the optimal operation point of maximal (100%) sensitivity and specificity - a higher detection score implies performance when detecting failure conditions.

Stage 1

In this section, it is presented all the details of the performed trials, PCAs, constructions of ASMs, and the statistical classifier (decision cascade). Note that 75% of collected data were used as train data, and the rest were used as test data. The selection of training and test data was made through cross-validation (*k-fold*). Best parameters for the ASMs were obtained through receiver operating characteristic (ROC) analyses.

Trials

A total of 12 healthy subjects, 3 females and 9 males, 25.33±6.33 years old, 66.92±10.07 kg, 1.74±0.11 m, performed three different trials, namely: i) Walk forward (WF) (Fig. 5a); ii) walk in circle (both sides - clockwise and counterclockwise (CR and CL)) (Fig. 5b); iii) walk forward bypassing an obstacle (right and left - OR and OL) (Fig. 5c). All trials were performed at a gymnasium, and they were repeated three times without a simulated fall and three more

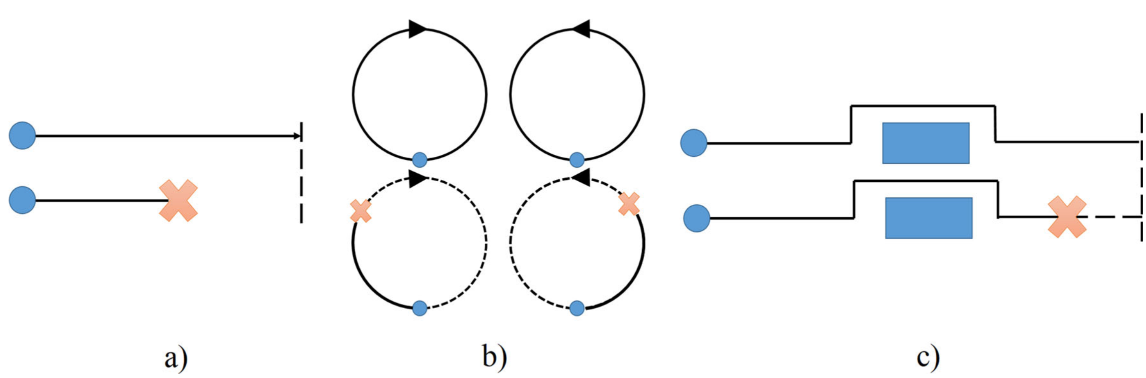

Fig. 5 Subject (dot) walks: **a** forward; **b** in circles; and **c** forward bypassing an obstacle (Top - w/o fall; Down - w/ fall where the fall's location is represented by the X)

Table 1 Classification of collected data (NG - Normal Gait)

Locomotion mode	Description of observations
Walk forward (WF)	NG from WF trials
Global	NG from WF, OR, OL, CR, and CL trials
Pre-fall (PF)	Gait cycle before the fall's situation
Fall (F)	Fall's situation

times with a simulated fall, which is a fall ordered by the responsible of the trials and does not occur in normal daily life situations. The subjects fell forward onto mattresses placed along the trial path.

PCA

The PCA previously described was performed four times. One for each locomotion mode collected during the performed trials. The designation adopted for each locomotion mode is available on Table 1, accompanied by a description of gait observations. This discrimination was carried out with the purpose of classifying different states of human activity, in particular in the fall's domain.

ASMs

Four ASMs, one for each locomotion mode (Table 1) were developed. Each ASM contains as many stereotypical variables as the relevant metrics selected by PCA for each locomotion mode. Simply put, if the PCA selects 20 variables for WF locomotion mode, the ASM will contain 20 stereotypical variables. It was also necessary to perform a ROC analysis to determine empirically the z, M, and N values for the different situations and test setups listed in Table 2. For each ROC analysis, the z value ranged from 1 to 5, M ranged from 3 to 6, and N ranged from 1 to 6. The chosen criterion to select the best combination of parameters was the minimal Euclidian distance [34].

Table 2 Different ROC analyses and their considerations

Designation	Training data	Description of pre-fall's data
ASM WF**	WF	not used in the tests
ASM WF*	WF	non-normal gait
ASM WF	WF	normal gait
ASM Global*	Global	non-normal gait
ASM Global	Global	normal gait
ASM Fall	F	normal gait
ASM PF△	PF	different from other types
ASM PF	PF	normal gait

Decision cascade

The decision cascade, which is a statistical classifier based on the constructed ASMs, has the intention of classifying a motion period as one of four things, namely: 1) normal gait. 2) Fall (F). 3) Pre-Fall (PF) step. And 4) other type. Besides, two considerations were made separately. The first consideration is to treat PF's data as normal gait like WF and Global's data (Case 1). The other consideration is to deal PF's data as different from F, WF and Global's data (Case 2). The decision cascade is shown in Fig. 6 and its explanation is given below.

As a first step, it was decided to check if the motion period described by the relevant metrics can be considered as normal gait. If a non-failure happens, then the process is stopped and the motion period is labelled as "Normal gait". Otherwise, it is necessary to verify other conditions. The first condition to be checked is the falling situation. In this situation, a fall is detected if a non-failure situation is detected, which means that the motion period should be in accordance with the aforementioned parameters of the F's ASM. If a failure is detected in the F's ASM, then the PF's condition is the last one to be verified. Once again, if a failure is detected, the final answer is "Other" which will label the motion period. Otherwise, a PF's motion period is detected. Herein, test data was used to verify the accuracy of the decision cascade.

Stage 2

Concerning the CNN, which is a classifier by nature, it is not necessary to perform previous procedures presented in Section "Stage 1". This time, each gait cycle was characterized by a $n \times m$ matrix, where each column (m) represents a metric, and each row (n) a sample. As in Stage 1, the same training data was used to train the CNN, and the same test data was used to get the evaluation performance of the classifier. Finally, two neural networks were trained and tested for both Cases 1 and 2 described in the previous section. Results of the accuracy were obtained for both situations.

Stage 3

A subject, male, 23 years old, 1.83 m, 65 Kg, performed a simple walking trial where at the end he could fall on a sofa or stop. A total of six trials were performed, where in three the subject simulated a fall, and in the other three he just stopped instead of fall. This walking trial consisted in walk forward, turn to the right, climb a small step, and stop

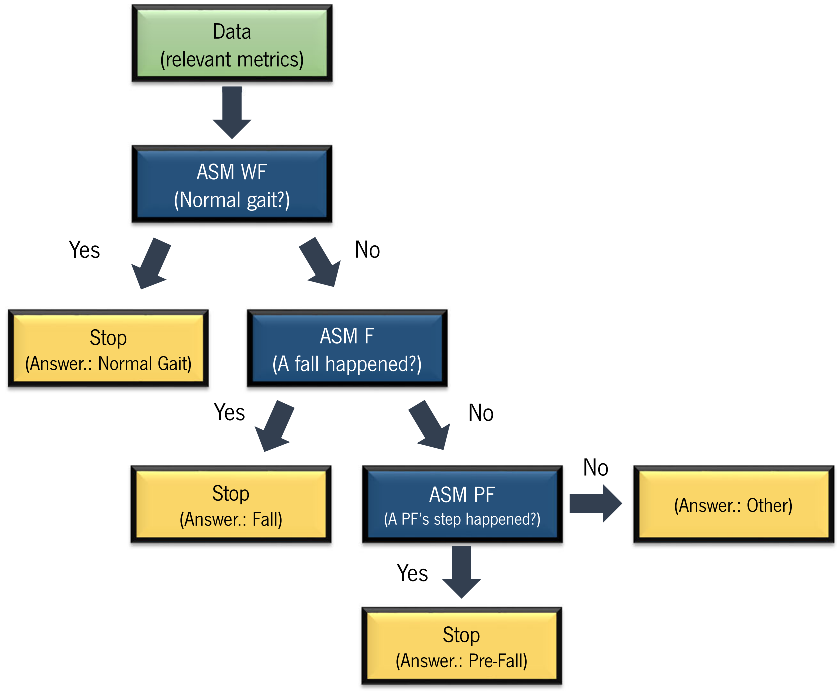

Fig. 6 Decision cascade to classify collected motion periods

or fall on the sofa in the delineated finish line. Figure 7 depicts the top view of the walking trial. Note that to climb a small step is a perturbation relatively to the data used to train the fall and pre-fall detection system. Similarly to Stages 1 and 2, Case 1 and Case 2 were also considered. Results of the accuracy were obtained for both situations and for both classifiers. For CNN, in Case 1, two labels were used (Normal Gait - 1; Fall condition - 2). In Case 2, there were three labels (Normal Gait - 1; Fall condition - 2; Pre-Fall condition - 3).

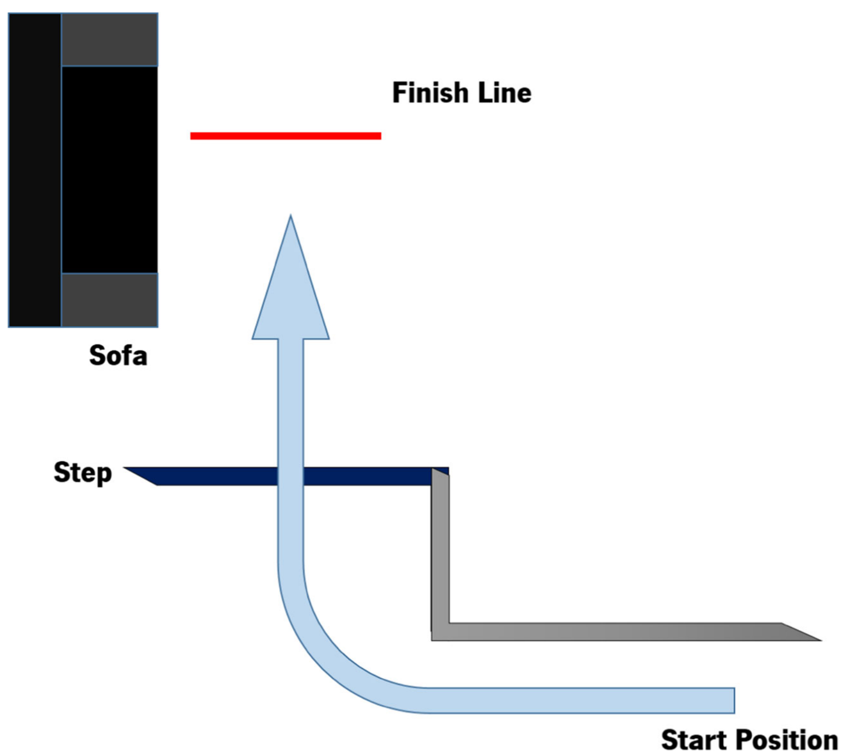

Fig. 7 Top view of the walking trial performed in Stage 3

Table 3 Main outcomes obtained from PCA

Locomotion mode	No. of extracted metrics	No. of observations
Global	41	970
WF	44	129
PF	45	135
F	30	134

Results

Stage 1

PCA

PCA was used to reduce the number of metrics for each locomotion mode, in order to reduce the computational cost. From 228 metrics, these procedures lead to 61 non-repeatable metrics and 25 common metrics between locomotion modes. Table 3 contains the number of extracted metrics per locomotion mode as a result of the application of PCA, as well as the number of observations per locomotion mode obtained from all performed trials. Taking into account the number of initial metrics (228), only the PCA for the "Global" locomotion mode had more observations (970) than initial metrics. Appendix contains the extracted metrics per locomotion mode.

ASMs

Concerning the construction of ASMs, 75% of each locomotion modes' data were used as training data. So, from 129 WF gait cycles, 97 were used as training data. From 970 Global gait cycles, 727 were used. 101 PF motion periods were used in a total of 135, and 100 F motion periods were used from a total of 134. An ASM was constructed for each locomotion mode. Each ASM contains as many stereotypical variables (ASMs) as the relevant variables selected by PCA for each locomotion mode (Table 3). A set of eight ASMs were constructed, and a total of eight ROC analyses were performed. Table 4 contains the best combination of parameters for each ROC analysis of each ASM (Table 2), as well as the value of the minimal Euclidian distance. On the other hand, Table 5 contains the values of the TPR, SPC, DS, 1-TPR, and 1-SPC for each ROC.

Table 4 Results from each ROC analysis

ASMs	z	M	N	Minimal Euclidean distance
ASM WF**	3.2	5	6	0
ASM WF*	3.4	3	2	0.2874
ASM WF	2.8	6	6	0.0097
ASM global*	3.2	3	1	0.2988
ASM global	4.2	4	1	0.0194
ASM fall	1.7	6	4	0.2553
ASM PF△	1.8	5	4	0.6018
ASM PF	3.4	5	1	0.0194

Table 5 Assessment parameters of each ROC analysis

Parameter	ASM WF**	ASM WF*	ASM WF	ASM Global*
TPR	100%	75%	100%	75%
SPC	100%	85.82%	99.03%	83.64%
DS	1.41	1.14	1.407	1.12
1-SPC	0%	14.18%	0.97%	16.36%
1-TPR	0%	25%	0%	25%
Parameter	ASM Global	ASM Fall	ASM PF△	ASM PF
TPR	100%	81.55%	45.95%	100%
SPC	98.06%	82.35%	73.53%	98.06%
DS	1.4006	1.159	0.8671	1.4006
1-SPC	1.94%	17.65%	26.47%	1.94%
1-TPR	0%	18.45%	54.05%	0%

Decision cascade

The order to check or classify the motion period was decided based on the results of Stage 1. The WF's ASM obtained the best results, even when compared to the results of the Global's ASM. Then, between F's ASM and PF's ASM, the first one had better results, which lead to the structure of the decision tree presented in Fig. 6. A total of 343 motion periods were used (WF - 32; Global - 243; PF - 34; F - 34) to test the decision cascade. The results of Case 1 are available on Table 6. In this consideration, the parameters used for WF's ASM were z=3.4, M=3, and N=2, and the parameters used for PF's ASM were z=1.8, M=5, and N=4. In this Case, the results were very good. 334 motion periods were accurately classified in a total of 343. PF's data were classified as normal gait mostly. Only 9 motion periods were identified as "Other". The accuracy of the decision cascade was 97.38%. In the Case 2, the parameters of the WF's ASM were z=2.8, M=6, and N=6,

Table 6 Results of the decision cascade for case 1 (NG-Normal Gait; LM - Locomotion mode)

LM	NG	F	PF	Other	Correct	Success rate(%)
WF	32	0	0	0	32	100%
Global	242	0	1	0	243	100%
F	0	26	0	8	26	76.47%
PF	32	0	1	1	33	97.06%

Table 7 Results of the decision cascade for case 2 (NG-Normal Gait; LM - Locomotion mode)

LM	NG	F	PF	Other	Correct	Success rate(%)
WF	29	1	0	2	29	90.63%
Global	207	2	3	31	207	85.19%
F	0	26	0	8	26	76.47%
PF	17	2	10	5	10	29.41%

Table 8 Main outcomes of the stage 2 - case 2 (input image size: 100x41; NG-Normal Gait; LM - Locomotion mode)

LM	NG	F	PF	Total	Success rate(%)
WF&Global	254	0	21	275	93.26%
F	0	34	0	34	100%
PF	4	0	30	34	88.24%

and the parameters used for PF's ASM were $z = 3.4$, M=5, and N=1. From the 343 used motion periods, 272 were accurately classified (Table 7). Hence, under these circumstances, the accuracy of this decision cascade was 79.3%. Figure 8 depicts snapshots of subjects in three different locomotion modes (WF, PF, and F), as well as examples of ASMs of "Mag_Z_2" with test trials/motion periods.

Stage 2

Only the 41 extracted metrics from the Global PCA were used in the CNN, as the number of observations (970) largely outnumber the number of variables (228) [41]. Thus, each motion period is represented as a matrix with 100 rows (samples) and 41 columns (metrics). For Case 1, the trained CNN was able to achieve 100% of accuracy with the test data, exemplarily distinguishing the normal gait from fall's situations. In Case 2, the accuracy obtained was 92.71%. All F's motion periods were all classified correctly. In a total of 34 PF's motion periods, 30 were well identified and 4 were considered as normal gait. 254 normal gait cycles were accurately classified, and only 21 were considered as PF's motion period. The results are available in Table 8.

Stage 3

The accuracy of the statistical classifier was 83.33% (45.83%) in Case 1 (Case 2). Concerning the CNN classifier, the accuracy was 91.67% (75%) in Case 1 (Case 2).

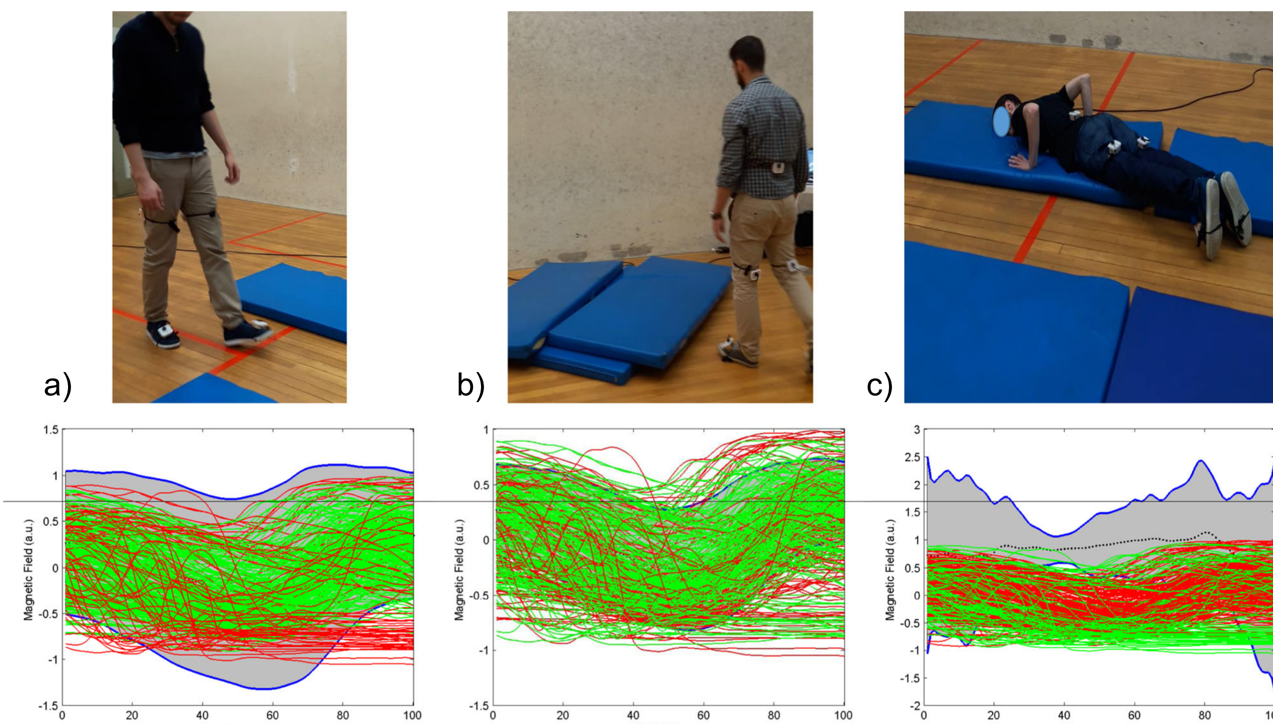

Fig. 8 Locomotion mode: **a** WF; **b** PF; and **c** F (Top - Snapshots of subjects in the respective locomotion mode. Down - Mag_Z_2 ASMs for each locomotion mode with test trials/motion periods)

Discussion

The PCA proved to be very important. It allowed to reduce the number of metrics from 228 to 61 non-repeatable metrics and to 25 common metrics between locomotion modes. This reduction is expected to only choose relevant information to continue to the next steps, but also to reduce the computational cost and thus shorten the processing time. Another important fact about these results is the high predominance of the Mag and metrics derived from Mag in the outcomes of PCAs (Appendix). Obviously, this can be a limitation in future works due to the ferromagnetic influences in indoor environments. Furthermore, only one PCA had more observations than variables/metrics. However, the results are close to each other. Concerning the results of the decision cascade, PF's data are very close to normal gait data (WF & Global). Case 1's results were optimal. On the other hand, Case 2's results were not as accurate.

Results of the statistical classifier and the CNN were very impressive and promising due to the high accuracy exhibited by both classifiers, and also due to the used amount of data. It was expected that the CNN would have better results since it is a machine learning solution tailored for this type of classification problem. In fact, in both scenarios, that was verified. In Case 1, the accuracy was 100% for the CNN and 97.38% for the statistical classifier. On the other hand, in Case 2, the accuracy was 81.92% for the CNN and 79.3% for the other classifier. However, in the authors' opinion the difference is quite small between values. One fact that highlights the ASMs is the fact that only the statistical classifier can indicate the moment of failure, which is truly important to better understand the human gait and to direct studies to more specific parts of it. This is required in order to gain a deeper understanding of fall prediction. Note that conceptually ASMs bring the possibility to be easily connected to motor commands to generate movements. This way motor generation and perception are joined together. This is an important aspect which the authors want to explore. In turn, CNN's results are very impressive and demonstrate that, in fact, PF's data have differences from normal gait. 30 (88.24%) of the 34 PF's motion periods were well classified. Perhaps, more data will help the statistical classifier to achieve better results under these circumstances. Taking into account the results of Stage 3, it is possible to claim that CNN (Case 1 - 91.67%; Case 2 - 75%) had a better performance over the statistical classifier (Case 1 - 83.33%; Case 2 - 45.83%) again. The performed trials had different movements from those recorded previously to construct both classifiers. The inclusion of a step, a curve, and a fall on a sofa, situations not taught *a priori* to the classifiers, make classification much more difficult for classifiers. Even, in this situation, the fall is not complete, because, in previous trials, the fall ended near the ground, which did not happen in this particular case. So, it was expected that the accuracy values for both classifiers were lower.

Conclusion

The major concepts of human gait classification were demonstrated offline and detailed comparisons were evaluated due to the implementation of two different methods present in literature, namely: ASMs and CNNs. From these results, it was concluded which is the most adequate procedure to apply in the human classification. In fact, it was concluded that the combination of different types of metrics provides a robust tool for detection of user's locomotion since each type of feature contributes with distinct information regarding the gait pattern. Additionally, it was concluded that the selection of the most discriminative features contributes to reduce the computation cost of this process. In this case, PCA revealed itself as an important procedure in this metrics' reduction. According to PCA, the results from this part revealed that Mag's sensors or metrics derived from this sensor are relevant. However, this can be dangerous if the IMU-based system is used in indoor environments where the ferromagnetic influence is variable. Concerning the classification phase of the locomotion mode recognition, the CNN classifier was implemented due to its advantages as pointed out in the revised studies. Its results were better than the statistical classifier. However, in the way it was implemented, it is not possible to know when a change is detected. On the other hand, the statistical classifier provides this information.

As future work, it is necessary to realize experiments of subjects walking in other different locomotion modes, such as ascending/descending stairs; start/stop walking; sit-to-stand/stand-to-sit; walking or with changes in speed. As well as collecting data from different types of fall. It is intended to have a system capable not only to inform if a normal gait or a fall or pre-fall's situation is happening, but also how it is happening and what the subject is doing. Also additional data from more trials will increase the classifier's accuracy. In the case of the CNN, it requires a huge amount of data in order to the results being more accurate. The implementation of the classifiers was only offline. Nevertheless, as future work, an online implementation of these classifiers in the IMU-based system would be a great step to a new and innovative product as long as the results of the classifiers with new and more data were promising. Regarding to the classification of falls, the confirmation of potential fall situations in real-time is pretended, however it will require that the extraction of information in online mode is the same as in offline mode. This article wanted to demonstrate a proof of concept and did not focus on some technical issues that an online implementation would demand. Thus, this application would be able to confirm potential fall situations, while discriminating between normal gait and a pre-fall situation (high fall risk) during walking.

It is also suggested an additional reduction of the metrics so that the computational cost decreases and, therefore, the data processing is faster. Given the results, it is possible to retain that there are metrics that never leave the limits of their ASMs. Therefore, a study on the influence of the reduction of the initial 228 metrics on the accuracy of the classifier should be done. Another statistical method, which also extracts the relevant metrics, must be experienced. The metrics excluded in this study (e.g. stride length, walking velocity and other periodic metrics) should also be included in a future study. Moreover, a study about the time of detection of fall and pre-fall's situations in real-time will be truly important, as well as the addition of actuation strategies.

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Compliance with Ethical Standards

Conflict of interests The authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent Informed consent was obtained from all individual participants included in the study.

Appendix: Extracted metrics per locomotion mode

Extracted metrics through the four PCAs (one per locomotion mode) are here presented. Tables 9, 10, 11, and 12 correspond to extracted metrics from PCAs that used WF, Global, PF, and F data, respectively.

Table 9 Relevant metrics identified (44) from PCA (WF Data)

AE_Acc_Z_1	AE_Mag_Y_2	AE_Gyr_Y_1	AE_Acc_Y_4
AE_Gyr_Z_1	AE_Gyr_X_4	AE_Mag_X_1	AE_Gyr_Y_4
AE_Acc_X_1	AE_Mag_Y_1	AE_Mag_Y_3	AE_Acc_Y_1
AE_Mag_Z_1	ASMA_4	ASMA_5	Acc_Y_4
Acc_Y_5	Acc_Z_4	Gait_Events	Gyr_X_5
Gyr_X_4	Mag_X_1	Mag_Z_2	Mag_Z_4
Mag_Z_1	Mag_X_3	Mag_Z_3	Mag_X_5
Mag_X_4	Mag_X_2	Mag_Y_4	SMA_4
SVM_5	SVM_4	SVd_4	SMA_5
WD_Mag_Z_4	WD_Mag_X_1	WD_Mag_X_3	WD_Mag_X_5
WD_Mag_X_2	Z2_Vert_Acc_4	WD_Mag_X_4	WD_Mag_Y_4

Table 10 Relevant metrics identified (41) from PCA (Global Data)

AE_Acc_X_1	AE_Gyr_Y_1	AE_Mag_X_1	AE_Mag_Z_1
AE_Acc_Z_1	AE_Gyr_Z_1	AE_Mag_Y_1	AE_Gyr_Y_4
ASMA_5	ASMA_4	Gait_Events	Mag_Y_2
Mag_X_5	Mag_Z_5	Mag_Z_2	Mag_Y_4
Mag_X_3	Mag_Y_5	Mag_X_2	Mag_X_4
Mag_Z_4	Mag_Z_3	Pitch_1	Pitch_2
Pitch_3	Pitch_4	SVM_5	WD_Mag_Y_4
Mag_X_1	Mag_Z_1	WD_Mag_Y_5	WD_Mag_Z_4
WD_Mag_Z_1	WD_Mag_X_2	WD_Mag_X_4	WD_Mag_Z_3
WD_Mag_X_1	WD_Mag_X_5	WD_Mag_Z_2	WD_Mag_X_3
Yaw_5			

Table 11 Relevant metrics identified (45) from PCA (PF Data)

AE_Mag_Y_1	AE_Acc_Y_1	AE_Mag_Z_1	AE_Acc_Z_1
AE_Gyr_Y_4	AE_Gyr_X_1	AE_Gyr_X_3	AE_Gyr_Y_1
AE_Gyr_Z_3	AE_Gyr_Z_1	AE_Mag_Y_3	ASMA_5
ASMA_4	Gait_Events	Joint_Ang_L	Mag_X_1
Mag_Z_2	Mag_Z_1	Mag_X_4	Mag_X_5
Mag_Y_4	Mag_Y_5	Gyr_Z_4	Mag_Z_5
Mag_X_3	Mag_X_2	Mag_Z_3	Pitch_1
Pitch_3	Pitch_2	Pitch_5	SVd_4
SVM_5	WD_Mag_X_5	WD_Mag_Z_4	WD_Mag_Y_5
WD_Mag_X_3	WD_Mag_X_2	WD_Mag_Z_3	WD_Mag_Z_2
WD_Mag_X_1	WD_Mag_X_4	WD_Mag_Z_1	WD_Mag_Y_4
Yaw_5			

Table 12 Relevant metrics identified (30) from PCA (F Data)

AE_Acc_X_2	AE_Gyr_Y_2	AE_Acc_X_3	AE_Gyr_Y_3
AE_Mag_Z_1	AE_Acc_Y_5	Gait_Events	Mag_X_1
Mag_X_2	Mag_X_3	Mag_Y_1	Mag_Y_2
Mag_Y_3	Mag_Z_1	Mag_Z_2	Mag_Z_3
Mag_X_5	Mag_X_4	Mag_Y_5	Mag_Y_4
Mag_Z_5	Mag_Z_4	WD_Mag_X_2	WD_Mag_Y_2
WD_Mag_Z_2	WD_Mag_Y_4	WD_Mag_Y_1	WD_Mag_Z_4
WD_Mag_Z_5	WD_Mag_Y_3		

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