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# Acceleration-based Gait Analysis for Frailty Assessment in Older Adults

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## ABSTRACT

Frailty in older individuals has been a hot research topic in the past two decades. This syndrome of physiological decline is characterized by damage to physical function. In the literature, walking speed and gait variability have been discussed and identified as major indicators of frailty. Short walking tests under supervised conditions are frequently considered when assessing the frailty status, where the subject is instructed to walk a certain distance, and the speed and temporospatial features are compared to thresholds. In this paper, we propose a more generalized and fully automated approach using wearable sensors, by suggesting a set of parameters extracted from acceleration signals. The interconnections between these variables, which are related to the gait quality and the frailty trajectory of the subject, are investigated. This study was done on older adults of diverse profiles, in free-living conditions during their daily routine, without any predefined protocol.

## 1. Introduction

The frailty syndrome manifests as disastrous declines in health and physical function, and increases the vulnerability of the person. It is known for its high prevalence in older adults and its complicated symptoms [6]. Accordingly, it constitutes an emerging public health priority, while the highest healthcare costs in industrialized countries are due to medical consumption by frail seniors [8].

Frailty has been a trending research topic in the past two decades [9, 25, 7]. Fig. 1 illustrates the model of this sickness and its different stages. The elderly person goes through four levels: (a) Robust (full performance), (b) Pre-frail (clinically silent), (c) Frail (progressive clinical worsening), and (d) Disabled (lack of autonomy and serious consequences). Two curves are plotted as a function of age, namely (i) normal aging and (ii) accelerated aging. The curve representing rapid weakening in the second process is framed in black (dash-dotted box) in the same figure. During this period called the “Frailty time-window”, which varies between older adults, a transition from robustness to frailty, and then to disability, occurs.

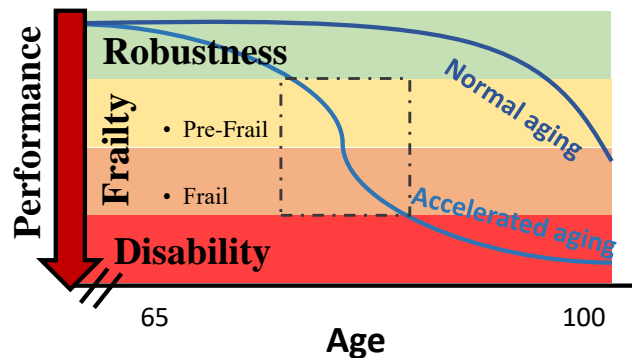


Fig. 1: The frailty model is divided into different stages. The dash-dotted box represents the frailty time-window, *i.e.* the period between good performance and disability, which is subject-dependent.

Fried *et al.* proposed a phenotype [9], which is defined by the presence of three of the following criteria: unintentional weight loss, exhaustion, low physical activity, slow walking speed, and weakness. Among these features, gait speed, which is the ratio of distance walked to time taken, is declared as one of the most relevant indicators. This variable is not only a predictor of health-related well-being outcomes, but also one of the strongest predictors of incident disability [23]. Middleton *et al.* described walking speed as a robust measure for physical function monitoring, and provided several recommendations on

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procedures to evaluate this variable, like optimal distance, experimental protocol, and so on [16]. Furthermore, Castell *et al.* showed that a gait speed with a value exceeding 0.9 m/s excludes the presence of frailty, and with a value below 0.8 m/s, doubles its probability [5].

Now, walking is a complex activity of daily living (ADL) and cannot only be restricted to gait velocity. Other parameters may vary during the transition towards frailty. It is worth mentioning that gait recognition and analysis have been tackled in the literature [13, 30]. Several gait parameters were also inspected in the context of frailty assessment. For instance, Kressig *et al.* proposed a set of temporal and spatial features, including cadence, stride length and stance, to better understand the effect of frailty on movements [14]. Moreover, gait variability was targeted and associated with frailty in elderly people [17]. Additional variables like displacement and smoothness of the center of pressure trace were inspected [11]. Even though these features are informative, we still do not know much about the relationship between gait parameters and categorical frailty classes [27]. Further analysis is needed to define the correlation between a set of gait variables and frailty. Furthermore, there is lack of studies that consider walking indicators, excluding speed, to develop a reliable frailty classifier [22]. To our knowledge, fully automated systems, which identify walking periods and compute features from acquired signals under unsupervised conditions to predict the frailty status and to better target preventive interventions, have received little attention in the literature. Moreover, gait analysis has not been implemented in routine assessments of frailty status in older adults [27]. Consequently, for a better frailty analysis, we propose a machine learning system that depends on acquired acceleration data from wearable devices, which are widely-used for activity and health monitoring [10]. This system can operate in free-living conditions, by wearing a single accelerometer placed on the trunk of the human body during daily routine. Gait periods could be identified in real-time using a human activity recognition approach, like the multinomial decomposition algorithm (MDA) [2]. Afterwards, an ensemble of time-domain and frequency-domain features, is extracted from raw data representing the gait of the wearer of the device to assess gait quality and track the frailty conditions.

This paper is organized as follows. The next section briefly introduces the gait analysis framework in elderly people, and justifies the choice of the proposed method. Section III is devoted to data collection, as well as material and methods. Section IV illustrates and discusses the experimental results before concluding the paper in section V.

## 2. Gait Analysis Framework

We shall now explore the different axes of human gait in older adults. The stance phase starts from the moment the foot touches the ground to the moment the same foot leaves it. This phase constitutes around 60% of the gait cycle. The swing phase starts when the foot leaves the ground and ends when it touches the floor again, constituting the remaining 40% of the cycle. Both phases lead to the stride time (gait cycle). Double

support is the period in the gait cycle when both feet are in contact with the floor. It occurs twice in the cycle and it changes with speed. A detailed illustration can be found in [28]. In the literature, these features were considered to evaluate frailty conditions [14, 3]. Moreover, gait variability, characterized by parameters such as stride time, stride length and step width variability, was associated with frailty in older adults [17]. The degree of variability might be more closely linked to fall risk than average gait speed and stride time [18, 12]. Gait mats with force plates and computerized walkways are used to measure the aforementioned features. Subjects complete several trials under supervised conditions, while walking at a self-selected usual pace (and/or fast pace) toward a visual target placed at the end of the walkway. Reflective markers and wireless sensors can be placed on the heel and the lower limb segments for example. Besides, some devices like McRoberts' MoveTest are developed for unobtrusive assessment of physical performance under supervised conditions [15]. When worn on the lower back, it enables elderly subjects to perform short physical performance tests such as Timed Up & Go (TUG) Test, with a pre-defined protocol to facilitate execution. The device then provides qualitative evaluation.

It can be seen that the aforementioned approaches are hardly applicable during daily routine in free-living conditions. Using the corresponding equipment is not a practical solution for community-dwelling seniors on a regular basis, and the authorized team conducting the analysis may not always be available to ensure the efficient execution of the trials. Spatial features, such as step width and stride length to name a few, might not be estimated accurately using a single accelerometer. Additionally, computing gait variability under unsupervised conditions might lead to erroneous results. The subject has to complete a set of instructions with a pre-defined pace in order to obtain a clear gait pattern resulting in an efficient gait variability calculation. This is not the case when he is walking on his own in real-world situations. Besides, it is worth mentioning that the use of stance, swing, and stride in the same set of features is somewhat redundant and may not add knowledge to the classifier, since they are correlated to each other in some way (stride is the sum of the stance and swing phases). Further analysis is needed to define a processing unit which is able to automatically detect the transition between frailty classes under unsupervised conditions using a set of descriptive and heterogeneous gait indicators, without being limited to the statistical significance of the aforementioned parameters. Consequently, we propose a fully-automated acceleration-based approach which computes an ensemble of features to assess the frailty level.

## 3. Materials and Methods

### 3.1. Population and Data Characteristics

To conduct the study, two datasets from two projects were merged to constitute one final dataset called GAnFA (which stands for Gait Analysis for Frailty Assessment). The first dataset is called ActFreeLi (Activities in Free Living conditions). It consists of acceleration data that were collected by our research team, using a wearable device developed by

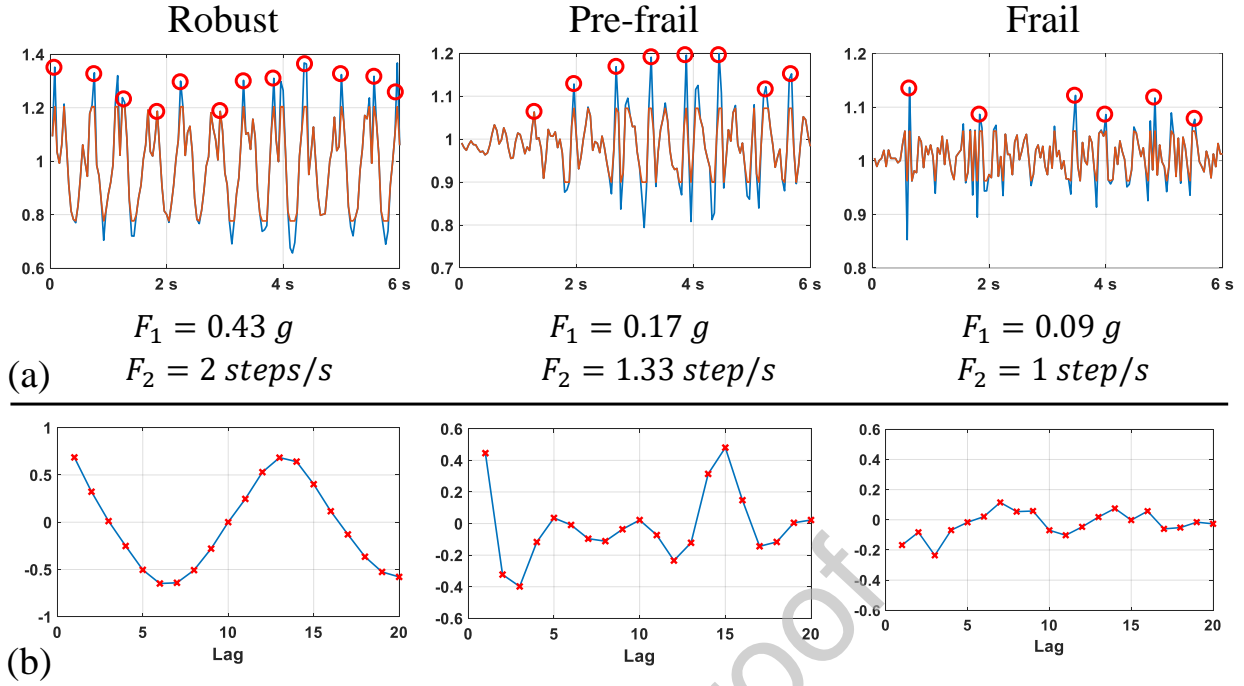


Fig. 2: (a) Acceleration magnitude as a function of time representing the gait of each category (steps in red circles) and (b) the corresponding autocorrelation of each time series as a function of the lag (in number of data-points).

the company RF-Track, based in Cesson-Sévigné, France. This device consists of a 3D accelerometer, namely LIS3DH, with a sampling frequency  $F_s$  equal to 50 Hz. Two positions were considered: waist-worn and necklace. Community-dwelling elderly over 80 years old were involved in this study. The use of acceleration signals belonging to these people was approved by the Ouest VI Institutional Review Board of Morvan University Hospital of Brest, France. Older adults residing in long-term care facilities were also recruited. Here, data collection was approved by the Ethics Committee of the University Hospital of Rennes, France. All participants gave their informed consent. The second dataset is the publicly available WWBS Metrics [21] from the FrailSafe project. Older adults of diverse profiles wore a sensorized smart vest during their daily routine, which was equipped with a 3D accelerometer configured at  $F_s = 25$  Hz.

Next, gait periods were cut using 6-second windows. This length (6 s) is appropriate for this task, since the proposed system operates automatically in unsupervised conditions. While shorter windows may discount some descriptive parts of the gait cycles, larger windows may contain some movements of a different activity, especially when the target is the analysis of the senior's gait in his daily routine. Finally, we down-sampled the ActFreeLi data by a factor of 2 (50 Hz  $\rightarrow$  25 Hz) and we combined them with the FrailSafe data to constitute GAnFA.

Acceleration data constituting GAnFA are time series of  $N = 150$  samples each (6 s  $\times$  25 Hz), representing 6 seconds of walking. These time series were distributed over 50 subjects whose age ranges from 70 to 92 years. Among these subjects, 16 were identified as being robust, 18 were diagnosed as pre-frail, and the remaining 16 as frail. The frailty status was indi-

cated using the five criteria of frailty phenotype.

### 3.2. Gait Parameters

We propose the use of six handcrafted features characterizing the gait of elderly people with regards to frailty status. In other words, the evolution of these parameters, which are detailed in this section, has to be correlated with frailty trajectory. Two components are considered in this analysis, namely the vertical component  $a_x(t)$  and the acceleration magnitude  $\|a(t)\|$  computed as follows:

$$\|a(t)\| = \sqrt{a_x^2(t) + a_y^2(t) + a_z^2(t)} \quad (1)$$

Fig. 2.a illustrates three time series, namely the acceleration magnitude, each one associated to a subject belonging to one of the three populations: (i) Robust, (ii) Pre-frail, and (iii) Frail. The orange part is the same acceleration signal after truncating the 25% lowest and highest data-points. Fig. 2.b illustrates the autocorrelation of each time series as a function of time-lag expressed in number of data-points (acceleration points).

**Feature  $F_1$ :** The range of orange signals decreases when the subject becomes frail, showing a decrease in movements intensity while walking.  $F_1$  is the 25% trimmed range of the acceleration magnitude. It is the range of the signal after excluding the highest and lowest  $k$  values, with  $k = \frac{N}{2} \times \frac{25}{100}$ ,  $N$  being the number of samples in the 6-second window as mentioned previously. Suppose that  $\|\hat{a}(t)\|$  is the truncated acceleration magnitude (orange signal in Fig. 2.a), hence:

$$F_1 = \max(\|\hat{a}(t)\|) - \min(\|\hat{a}(t)\|) \quad (2)$$

The use of trimmed estimators helps eliminate the influence of outliers. The accelerometer might induce some noise (due to mechanical or other reasons), which results in high peaks in the signals. This phenomenon may lead to erroneous results and justifies the use of truncated signals when calculating the range. Fig. 3 illustrates the violin plots corresponding to this feature. The median of the first class (Robust) is the highest, and decreases when the subject becomes pre-frail then frail.

**Feature  $F_2$ :** The cadence or steps rate over a fixed window length  $L$  (6 s in our case) constitutes the second feature  $F_2$ . Seeing that the accelerometer works on the principle of a mass on a spring, the spring is compressed or stretched when a step is taken. This produces a force corresponding to the acceleration (Newton's second law), which reaches a peak during this phase. Hence, the number  $D$  of peaks in acceleration signals corresponds to the number of steps performed by the subject. Therefore:

$$F_2 = \frac{D}{L} \quad (3)$$

Note that several techniques have been developed in the literature to detect peaks in a signal, like in [20, 1].

The values of both features ( $F_1$  and  $F_2$ ) are mentioned in Fig. 2.a for each of the illustrated acceleration signals. They decrease with the deterioration of the physical function. **It is worth mentioning that the cadence of very fit/healthy elderly and "transitioning to frailty" older adults were reported as  $1.86 \pm 0.14$  and  $1.76 \pm 0.21$  steps/s respectively in the literature, when calculated under supervised conditions using markers and walkways [14, 29]. Interestingly, the proposed feature  $F_2$  shows that this variable is around  $1.67 \pm 0.18$  steps/s for robust people,  $1.33 \pm 0.23$  steps/s for pre-frail elderly, and  $1 \pm 0.43$  for frail older adults, when calculated over 6 seconds using a single accelerometer in free-living conditions.**

**Feature  $F_3$ :** since walking is a cyclic activity, the periodicity of the signal should be taken into consideration. **Here, to identify the presence of cycles in the signal, the goal is the observation of similarity between  $\|a(t)\|$  and its delayed version  $\|a(t - \tau)\|$  where  $\tau$  is a time lag. Consequently, the autocorrelation which can be calculated as a function of  $\tau$ , is denoted by  $A(\tau)$  and is**

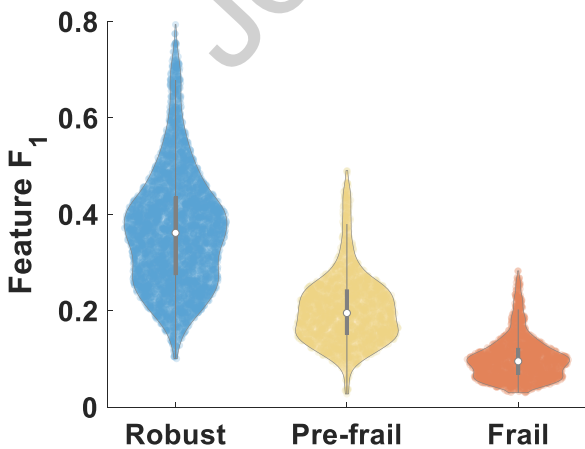


Fig. 3: The violin plot of feature  $F_1$ .

computed following three steps [4]:

$$\begin{cases} F_R(f) = \mathcal{F}\{\|\bar{a}(t)\|\} \\ M(f) = \|F_R(f)\|^2 \\ F'_R(\tau) = \mathcal{F}^{-1}\{M(f)\} \\ A(\tau) = \Re\{F'_R(\tau)\} \end{cases}$$

where  $\|\bar{a}(t)\|$  denotes the demeaned acceleration magnitude,  $\mathcal{F}$  is the fast Fourier transform,  $\mathcal{F}^{-1}$  its inverse, and  $\Re\{X\}$  the real part of  $X$ .

$A(\tau)$  is then normalized, by dividing its components by  $A(0)$  (its maximum value). It is clear from Fig. 2.b that  $A(\tau)$  ( $\tau = 1, \dots, T$ , with  $T = 20$ ) is regular for the robust (healthy) subject. However, the sinusoidal shape vanishes while heading towards the frail status, since the periodicity disappears in the acceleration signals, meaning that the gait loses its fluidity. The information carried by  $A(\tau)$  is encoded in a third feature  $F_3$ , by calculating the distribution entropy of this autocorrelation signal. The entropy quantifies the unpredictability or the randomness of  $A(\tau)$ , which is partitioned into 10 equal intervals of size  $W$ . If the number of points in the  $i^{\text{th}}$  interval is equal to  $t_i$ :

$$F_3 = \log(W) - \sum_{i=1}^{10} \frac{t_i}{T} \log\left(\frac{t_i}{T}\right) \quad (4)$$

**Feature  $F_4$ :** the dynamism of the elderly while walking might be an important indicator of frailty. To this end, we could monitor the sudden jumps in  $\|a\|$  during gait periods, which reflect, in some way, the variability of the time series. The goal behind this fourth feature is to count the number  $S$  of times where the absolute value of the difference between two consecutive acceleration samples exceeds a predefined threshold found by trial and error (in our case equal to 0.075 g). The total count is then divided by the total number of samples  $N$  to constitute  $F_4$ :

$$F_4 = \frac{S}{N} \quad (5)$$

**Features  $F_5$  &  $F_6$ :** here, the vertical component  $a_X(t)$  is concerned. A fitted AutoRegressive model (AR) to the time series could be relevant in gait analysis to detect physical weakening. This model predicts the future behavior based on the past. The time series  $a_X(t)$  (representing the vertical component) is explained linearly by its past values  $a_X(t - i)$ , a bias  $b$ , and a stochastic term  $\epsilon_t$  [19]:

$$a_X(t) = b + \sum_{i=1}^p \phi_i a_X(t - i) + \epsilon_t \quad (6)$$

$p$  is the order of the model and  $\phi_i$  are its parameters. Note that  $\phi_i$  is the  $i^{\text{th}}$  element of  $\phi$ . Eight AR models are estimated [26], from order 1 to order  $M$  ( $p = 1, \dots, M$ , with  $M$  equal to 8 in our case). Afterwards, two criteria are applied to choose the optimal order  $p$ , namely Akaike information criterion (AIC) or Bayesian information criterion (BIC). The smallest value for this order is selected. For example, when an AR model of order

Table 1: The resultant p-values of (i) Wilcoxon Rank Sum Test for each pair of populations and (ii) Kruskal-Wallis H Test, and the feature ranking of ReliefF with  $k = 5$  nearest neighbors.

Wilcoxon Rank Sum Test			Features	Kruskal-Wallis H Test	Relieff Ranking
Robust vs Pre-frail	Robust vs Frail	Pre-frail vs Frail			
< 0.001	< 0.001	< 0.001	$F_1$	< 0.001	2
> 0.05	< 0.01	< 0.001	$F_2$	< 0.001	4
< 0.001	< 0.001	< 0.001	$F_3$	< 0.001	5
< 0.001	< 0.001	< 0.001	$F_4$	< 0.001	3
< 0.001	< 0.001	< 0.001	$F_5$	< 0.001	1
< 0.01	< 0.001	> 0.05	$F_6$	< 0.001	6

$p = 3$  is fitted,  $\phi_{4,\dots,M}$  are set to 0. Then, two features are calculated to encode the set of AR model parameters. Feature  $F_5$  is the standard deviation  $\sigma_\phi$  of vector  $\phi$ :

$$F_5 = \sqrt{\frac{1}{p} \sum_{i=1}^p (\phi_i - \mu_\phi)^2} \quad (7)$$

where  $\mu_\phi$  is the mean value of  $\phi$ .

Feature  $F_6$  is the kurtosis  $\kappa_\phi$  of vector  $\phi$ , indicating whether the distribution of the AR model parameters is tight (smaller AR order) or flattened (higher AR order):

$$F_6 = \frac{\frac{1}{M} \sum_{i=1}^M (\phi_i - \mu_\phi)^4}{[\frac{1}{M} \sum_{i=1}^M (\phi_i - \mu_\phi)^2]^2} \quad (8)$$

Expressly, it identifies whether the tails of this distribution carry some extreme values or not.

The combination of cadence (feature  $F_2$ ) with the remaining five novel features characterizes the gait of older adults and will be used to predict their frailty status.

## 4. Experimental Results

### 4.1. Performance Evaluation

In this section, the discrimination power of the proposed features is examined. The aforementioned six features were first extracted from the 6-second acceleration windows of GAnFA. We started by the individual performance of each feature. The non-parametric statistical hypothesis test, namely Wilcoxon Rank Sum Test, was first applied to assess the statistical significance. Hence, for each feature, this test was applied following three pairs (X, Y), namely (Robust, Pre-frail), (Pre-frail, Frail), and (Robust, Frail). Additionally, the Kruskal-Wallis H Test, which is similar to the aforementioned test but can accommodate more than two groups, was also applied. The importance rank of features was evaluated using ReliefF algorithm with  $k = 5$  nearest neighbors [24]. Table 1 illustrates the corresponding results. The cadence ( $F_2$ ) is unable to differentiate between the robust and pre-frail populations. Meanwhile, the pre-frail and frail subjects do not differ significantly following feature  $F_6$  (the kurtosis of AR model coefficients  $\phi_i$ ). Nonetheless, the Kruskal-Wallis test reveals the statistical significance of all features when it comes to the tri-class classification, with a p-value below 0.001. The ReliefF ranking shows that the top

three features are  $\{F_5, F_1, F_4\}$ , i.e. the variability of  $\phi_i$ , the intensity of movements, and the dynamism.

Now, the goal is to see to what extent the combination of those parameters is able to predict the frailty status of an elderly person. Therefore, feature vectors were scaled using the sigmoidal transformation, affecting both the values and the distribution of these features in the space:

$$\widehat{F} = \frac{1}{1 + \exp(-\frac{F - \mu_F}{\sigma_F})} \quad (9)$$

where  $\widehat{F}$  is the scaled feature vector,  $F$  is the original feature vector,  $\mu_F$  is the mean value of  $F$ , and  $\sigma_F$  is the standard deviation (SD) of  $F$ .

We first applied the principal component analysis (PCA) technique for graphical representation purposes, by reducing the dimensionality while minimizing the information loss. Fig. 4 illustrates the data distribution following the three principal components. Three clusters can be observed: the first one (blue points) with a (0.33; -0.03; 0.01) centroid represents the robust population, the second one (yellow points) with a (-0.13; 0.36; 0) centroid represents the pre-frail population, and the third one (orange points) with a (-0.47; -0.18; 0) centroid represents the frail population. Although a certain intersection can be seen between each pair of clusters, the populations are quite separable.

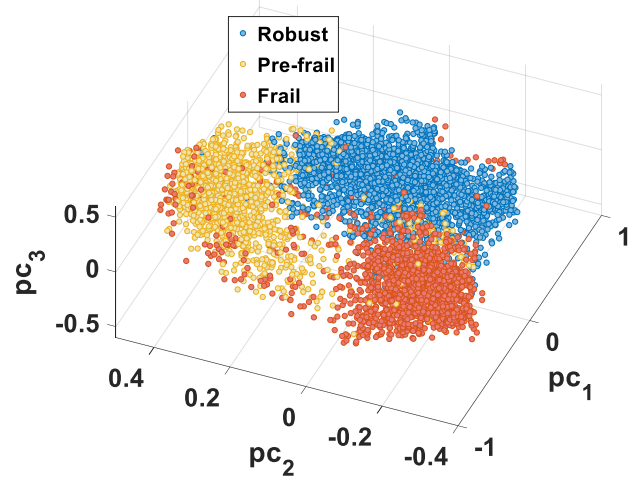


Fig. 4: Data distribution of the three populations following three principal components.

Table 2: The configuration (chosen parameters) of each classifier

Classifier	Configuration
NN	1 hidden layer, 15 neurons, logistic*
SVM <sub>R</sub>	Radial basis function kernel
KNN	5 nearest neighbors ( $k = 5$ )
RF	$n_{\text{trees}} = 10, d = 10^{\ddagger}$
GBM	$n_{\text{estimators}} = 100, d = 5^{\ddagger}, l = 0.1^{\dagger}$

\* Activation function –  $\ddagger$  Depth –  $\dagger$  Learning rate

Next, to quantify the discrimination power of the proposed features, several machine learning classifiers were considered and were fed by the scaled feature vectors of length 6, namely (i) a neural network (NN), (ii) Support Vector Machines (SVM<sub>R</sub>), (iii)  $k$ -Nearest Neighbors (KNN), (iv) Random Forest (RF), and (v) Gradient Boosting Machine (GBM). Table 2 shows the corresponding parameters for each classifier. Other less efficient classifiers were also tested (Naive Bayes and Linear Discriminant Analysis to name a few), but are not mentioned in this paper for readability purposes. Leave-Subject-Out (LSO) cross-validation was applied to ensure a fair evaluation. Table 3 illustrates the different results in terms of accuracy. The accuracy of the aforementioned classifiers ranges from 86.26% to 88.5%. SVM<sub>R</sub> is the top performer, where on average, an accuracy of 88.5% was achieved per subject. The NN is a close competitor with an accuracy of 88.18%. It is worth mentioning that the number of trees  $n_{\text{trees}}$  of RF is relatively small, compared for example to GBM which uses 100 estimators. Increasing  $n_{\text{trees}}$  indefinitely might increase the accuracy of RF, but may also induce overfitting which prevents the generalization of the model (the ability of a trained model to classify unseen data). Explicitly, with more than 20 estimators, the accuracy of RF exceeds 88%, and it is somewhat saturated beyond 45 estimators. The achieved accuracy in this case may not reveal the reliability of the system in real world situations.

Fig. 5 illustrates the confusion matrix, based on the output of SVM<sub>R</sub> (the best classifier). The columns represent the target class or the ground truth, while the rows represent the predicted class or the output of the classifier. The diagonal elements constitute the correct decisions. For instance, 92.3% of gait signals belonging to the robust elderly subjects are well classified. However, 5% of those signals are misclassified as pre-frail and the remaining 2.7% as frail. The highest confusion occurs with the pre-frail class for which 11.3% of signals linked to this population are classified as robust, and 2.1% of those signals are categorized as frail. Furthermore, 8.4% of signals labeled as frail were classified as pre-frail by SVM<sub>R</sub>.

#### 4.2. Discussion

This work analyzes the relationship between heterogeneous gait parameters and the frailty status of elderly people in free-

Table 3: Results of different machine learning classifiers

Classifier	NN	SVM <sub>R</sub>	KNN	RF	GBM
Accuracy (%)	88.18	<b>88.5</b>	86.26	87.26	87.51

		Actual class		
		Robust	Pre-frail	Frail
Output class	Robust	92.3%	11.3%	8.7%
	Pre-frail	5%	86.6%	8.4%
	Frail	2.7%	2.1%	82.9%

Fig. 5: Confusion Matrix resulting from SVM with a RBF kernel (SVM<sub>R</sub>).

living conditions during daily routine, unlike the aforementioned literature studies which focused on temporospatial features under supervised conditions. The previous sub-section revealed the efficiency of the proposed parameters, with an accuracy of 88.5%. This means that based solely on the proposed six gait variables, one can predict the frailty status with an accuracy of nearly 90%. This result is satisfying since frailty is much more than the gait analysis, and the ground truth is based on 5 different indicators. Besides, it is worth noting that the proposal of fully automated systems, which classify elderly into three frailty levels based on their gait, has received little attention in the literature [27]. ANOVA analyses and statistical significance are usually deployed for performance evaluation [17, 3]. Moreover, some studies were limited to a quantitative report of features for each population [14, 29]. In this paper, predictive models were considered and the discrimination power of features was quantified.

Now, the classification is a “frozen” process in this context, *i.e.* the prediction is done at a particular time (a specific day). However, the evolution of those parameters with respect to the frailty curve and the long-term surveillance are what matter the most. Therefore, the confusion matrix should be carefully interpreted. The elements outside of the diagonal are the rate of misclassified signals. A part of this confusion is informative and valuable for the analysis of the syndrome, and is not necessarily linked to the system deficiency. In fact, the Robust/Pre-frail and Pre-frail/Frail misclassification rates define the curve of the frailty trajectory. The 5% of robust older adults, who are classified as pre-frail by our model, but are robust according to the frailty phenotype, might very well be showing signs of physical weakening, and are likely to be considered as such by the aforementioned phenotype in the next few weeks. This finding is important for prevention and could help the practitioner by proposing an intervention in order to avoid serious consequences. The same remark holds for the 2.1% confusion between Frail and Pre-frail classes. As for the 8.4% misclassification rate, the gait of those seniors, who are frail according to Fried’s criteria, is still not completely damaged. These subjects present progressive worsening, and are on the verge of getting frail (see framed zone in Fig. 1). A rapid intervention is then needed to help the elderly in retrieving their physical condition and avoid any sudden turn towards disability.

In summary, this paper assessed the discrimination power of a novel set of gait parameters and its ability to (i) predict the

frailty status automatically and (ii) assess and detect the transition towards frailty. Our results are twofold: (i) the resultant confusion matrix is well correlated with frailty phenotype, (ii) the deviations from the target classes should be seen as important and useful clues in the frailty trajectory.

## 5. Conclusion

In this paper, we outlined the importance of gait analysis in frailty assessment using wearable sensors. Five different gait characteristics were discussed, namely (a) the intensity of the movements, (b) the steps rate, (c) the periodicity of the movements, (d) the gait dynamism, and (e) the representation of the gait as a time-varying process by fitting an AR model (represented by two features). Unlike previous studies which focused on temporospatial features calculated under supervised conditions, our method gives new dimensions to the gait analyses by calculating the set heterogeneous parameters during daily routine under unsupervised conditions. The SVM<sub>R</sub>, fed exclusively by six features, is able to predict the frailty status with an average accuracy of 88.5%. The results from 50 older subjects in real world conditions showed a correlation between the proposed gait parameters and frailty phenotype. The proposed model might also track the transition between frailty levels, and thus assist the clinician for a better assessment.

In a future work, angular velocity acquired from gyroscope could be studied, to see if it provides some added value to the proposed model. The analysis of postural transitions like sitting down and standing up is going to be a research topic.

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- A fully automated system for gait analysis in the context of frailty
- Extraction of original features describing the older adults' gait in regards to frailty status
- Assessment of frailty trajectory in elderly under unsupervised conditions during daily routine
- An added value in comparison with the standard frailty phenotype

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**Declaration of interests**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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