Title page

Title:

Relevance of sex, age and gait kinematics when predicting fall-risk and mortality in older adults

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Abstract

Approximately one-third of elderly people fall each year with severe consequences, including death. The aim of this study was to identify the most relevant features to be considered to maximize the accuracy of a logistic regression model designed for prediction of fall/mortality risk among older people.

This study included 261 adults, aged over 65 years. Men and women were analyzed separately because gender stratification was revealed as being essential for our purposes of feature ranking and selection. Participants completed a 3-m walk test at their own gait velocity. An inertial sensor attached to their lumbar spine was used to record acceleration data in the three spatial directions. Signal processing techniques allowed the extraction of 21 features representative of gait kinematics, to be used as predictors to train and test the model. Age and gait speed data were also considered as predictors. A set of 23 features was considered. These features demonstrate to be more or less relevant depending on the gender of the cohort under analysis and the classification label (risk of falls and mortality). In each case, the minimum size subset of relevant features is provided to show the maximum accuracy prediction capability.

Gait speed has been largely used as the single feature for the prediction fall risk among older adults. Nevertheless, prediction accuracy can be substantially improved, reaching 70% in some cases, if the task of training and testing the model takes into account some other features, namely, gender, age and gait kinematic parameters. Therefore we recommend considering gender, age and step regularity to predict fall-risk.

Introduction

Falls are the leading cause of injury in adults aged 65 or older (Jill Jin, 2018). One-third of older adults suffer from falling syndrome each year, with severe consequences, i.e. mortality, morbidity, disability and loss of independence (Tinetti et al., 1995) and significant financial implications, i.e. 3% of all people over 65 visit the Emergency Department due to a fall incident each year. Medical expenses related to falls in the elderly are estimated at € 675.4 million annually in the Netherlands (Hartholt et al., 2012). However, prevention is possible with appropriately designed intervention programs, i.e. ViviFrail, USPSTF (Ejupi et al., 2014). Therefore, early detection is the key to mitigate fall incidence and to improve the quality of life for elderly individuals (El-Khoury et al., 2013; Herwaldt and Pottinger, 2003; Rao, 2005).

Gait speed has been outlined in the literature as a useful clinical indicator of health status among very old people over 85 years (Toots et al., 2013) as well as a predictor of falls and mortality (Meyer, 2010; Studenski et al., 2011). However, gait is a complex motor activity with many measurable facets, apart from velocity-related parameters, that could be useful for fall or mortality risk identification (Moreira et al., 2015). Factors such as gait kinematics can improve prediction capability (Bridenbaugh and Kressig, 2011). In fact older adults at risk of falls tend to exhibit decreased stride length and single-limb support time and increased gait variability and double-limb support time according to the literature (Callisaya et al., 2010; Marques et al., 2018, 2017). Wearable sensors can be easily applied at the point-of-care and facilitate quantitative assessments in clinical or older-adult care environments (Özdemir and Barshan, 2014). Therefore, further research is recommended to improve fall/mortality risk prevention using wearable sensors as a stand-alone assessment tool or supplement to clinical tests (Ejupi et al., 2014; Howcroft et al., 2013).

Significant differences are observed in gait parameters regarding the gender of the subject, i.e., hip and knee angles (Guha Thakurta, 2016), step length and cadence (Frimenko et al., 2015) and gait variability (Kiss, 2012). Understanding gender factors that may contribute to falls could lead to personalized fall prevention (Voermans et al., 2007). In this study, appropriate sensor based features and regression, classification and clustering techniques are combined to enhance falls and mortality-risk prediction for males and females separately. The final aim is to provide clinicians with tools to improve services for elderly people at risk of falling or mortality as well as to increase preventive approaches and therapeutic interventions efficiency (Moreira et al., 2015). Moreover, the aging of the population is increasing in most European countries. Currently, simple gait parameters can be obtained with everyday devices such as wearable or smartphones that incorporate inertial sensors. The improvement of these devices may include other more precise parameters that will help to predict adverse events and, therefore, improve the quality of life of these people.

Methods

Subjects

A cohort of 261 subjects from an elderly population of 103 males (age: 76.7±5.9 yr, mass: 74.7±11.5 kg, height: 162.4±7.1 cm) and 158 females (age: 75.1±6.3 yr, mass: 69.3±12.3 kg, height: 152.2±6.6 cm) carefully extracted from the Toledo Study Healthy Aging database constitutes our original complete N261 dataset. F158 and M103 are, respectively, the female and male sub-cohorts that will be considered when performing analyses stratified by gender. The study methods have been reported elsewhere (Butcher et al., 2019; Garcia-Garcia et al., 2011). For cohort details and selection of participants see Appendix 1 of this previous work (Butcher et al., 2019).

Testing procedures

The subjects walked in a straight line, without obstacles at a self-regulated speed. The measurements were taken in a 3-meter section leaving some acceleration distance at the start and end of the path. All subjects underwent the same assessment. The subjects performed the test in their homes in order to replicate the way in which people walk in their usual environment. The study protocol was approved by the Clinical Research Ethics Committee of the Hospital Complex of Toledo, Spain. All study participants provided signed informed consent prior to their inclusion in the cohort.

Instrumentation

The walking test was performed with an inertial sensor, MTx (XSENS, Xsens Technologies B.V. Enschede, Netherlands), attached over the lumbar spine to record acceleration data. MTx comprises nine individual MEMS sensors: 3 accelerometers, 3 gyroscopes and 3 magnetometers, to provide drift-free 3D orientation as well as kinematic data: 3D acceleration and 3D rate of turn (rate gyro). As it has been proved in previous works, the system is suitable for reliable measurement of mean temporal-spatial parameters (Hamacher et al., 2014; Teufl et al., 2019).

The acceleration signal consists of gravitational and inertial components. The gravity component was subtracted to estimate the dynamic acceleration using the rotational matrix.

To extract representative gait features it is necessary to identify and separate the signal interval corresponding to the subject movement, which is accomplished by automatic peak detection. To eliminate unrepresentative peaks and facilitate obtaining the most prominent ones, an approximation using wavelet (Coif5 level 3) decomposition was made.

Output variables

The measured spatiotemporal parameters related to gait disorders (Brach et al., 2011; Karmakar et al., 2007; Menz et al., 2003; Moe-Nilssen and Helbostad, 2004; Montero-Odasso et al., 2011; Yang et al., 2011) were step and stride regularity, gait symmetry, approximate entropy (AE) and signal root mean square value (RMS), while frequential parameters were the harmonic ratio (HR) and total harmonic distortion (THD). All of these parameters were obtained for three directions: anteroposterior (AP), mediolateral (ML) and vertical (V) (Martínez-Ramírez et al., 2015). Numerical codes assigned to these spatiotemporal and frequential features (for the sake of a fast and easy identification) are summarized in Table 1, to which age, gait speed and gender have been added.

The Toledo Study Healthy Aging database also includes the history of falls in the last twelve months and information about those patients who died. These data allow us to distinguish between non-fallers and fallers (independent of the quantity of falls reported) and between people who died in the last five years and those who are still alive. All types of falls were recorded, both minor and most serious which could have required hospitalization. Deaths provoked by external factors were no taken into account in the database. Both outputs “falls” and “mortality” can be viewed as dichotomous output variables which will be used as classification labels (responses).

Classification and testing procedures

Although different training and classification techniques were considered and analyzed in depth, only results rising from a logistic regression model are presented in this paper. Logistic regression (Hosmer et al., 2013) is a method that models the log-ratio of the likelihoods (also known as logit) in a linear approach as follows:

$$ln \frac{P(X/C_1)}{P(X/C_2)} = W^T X + b$$

Here $P(X/C_i)$ is the likelihood of X belonging to class C_i ($i = 1$ for positive class and $i = 0$ for negative class); W is the d-dimensional weight vector (d is the number of features at hand), which is a vector orthogonal to the decision boundary, directed towards the C_1 positive class; and b is the bias, also called threshold, a scalar that decides the location of the decision boundary with respect to the hyperspace origin.

Logistic regression is a particularly well suited method whenever the response is a dichotomous variable and it has been largely used in medical applications (Avali et al., 2014; Bisaso et al., 2018; Zhou et al., 2015).

Following the usual procedure certain percentage of data (70%) is devoted to train the model, i.e., to calculate W vector and b scalar values, and the leftover data (30%) are set aside to estimate the model accuracy. Cross validation techniques are added in order to increase reliability in accuracy value: the whole dataset is divided into several folders (50) and different combinations between one folder for testing purposes and remaining data folders to train the model are considered. Accuracy value is calculated as the statistical mean value from those obtained for each train-and-test folder combination.

The 21 (= 7 parameters x 3 spatial axes) features obtained from accelerometers, as well as feature22=age and feature23= gait speed were normalized so that all of them present zero mean and unity standard deviation (Jayalakshmi and Santhakumaran, 2011).

When dealing with a large enough set of features, as is the case herein, it is important to rank their relevance with regard to the decision boundary estimation, since irrelevant features may lead to unnecessary computation without rendering higher accuracy. In fact, for a given dataset, the model accuracy increases with the number of features up to a certain point, beyond which the classification accuracy begins to drop. The optimal features subset is the minimum group of features able to produce a model with maximum accuracy.

Feature selection

One of the main aims of this work was to establish a ranking of features from which extract the optimal feature subset that leads to a minimum classification error, i.e., to perform a feature selection process (Saeys et al., 2007). The applied strategy, known as the sequential forward selection method (M. Narasimha Murty, 2015), begins with an empty candidate subset to which relevant features are sequentially added, in a relevance decreasing order, until the addition of further features does not produce any increase in accuracy. In each algorithm loop the previously obtained subset of relevant features is combined with, one by one, the remaining features and each combination is used to train the model and to test its accuracy. That combination with minimal error allows us to identify the next relevant feature, which is added to the subset. This method is much more consistent and robust than a simple proposal of features subset as done by Hua et al (Hua et al., 2018).

Since model train and test are carried out several times in a cross validation scheme, the optimal minimum subset is obtained as a mean subset, containing those features whose consistency surpasses a given threshold. Here every feature consistency is a weight in the range [0, 1] that indicates how many times this feature is identified as a relevant one.

As in any other wrapped selection model, both the optimal subset size and the features identified as relevant, and thus included in the subset, are directly related to the training method applied, which means that the optimal combination may vary if the training method is changed. In other words, the several subsets of ranked relevant features that will be shown later (Table 2) are closely related to (a) the method chosen for classification: logistic regression in all cases; (b) the output variable selected as the class label: “falls” and “mortality” were considered as responses; and (c) the dataset of predictors (features) used for training and validation.

Data analysis

Figure 1a shows the balanced behavior exhibited by fall distribution in the complete N261 database: the number (#133=48 men, 85 women) of adults who had fallen is very similar to the number (#128=55 men, 73 women) of those who did not report any fall in the previous year. This balanced trend (approximately 1:1) between fallers and non-fallers remains when the complete cohort N261 splits into F158 and M103 (Figs.1b and 1c). It is also worth noting the smooth distribution between males and females in both classes (fallers vs non-fallers), presenting an approximated ratio of 4:6.

Figure 1d shows the strongly imbalanced behavior exhibited by cohort N261 when mortality is chosen as the classification response: the number (#45=26 men, 19 women) of adults who died, and who belong to the positive class, is far smaller than the number

(#216=77 men, 139 women) of those who are still alive. The distribution of males/females in both classes (dead vs alive) is also very different: 6:4 among dead subjects, but 4:6 among alive. The imbalanced behavior between both classes remains when the analysis is performed with gender stratification (Fig.1e for F158 and Fig.1f for M103).

It is well known that imbalanced datasets can render a model in which minority class is ignored thus producing a high percentage of false negatives. To cope with this problem, a SMOTE (Synthetic Minority Oversampling Technique) algorithm was applied (Chawla et al., 2002). This method provides a mix between synthetic oversampling of the minority class (dead) and downsampling the majority class (alive). The combination of synthetic data added due to oversampling and real data neglected due to downsampling modifies the corresponding dataset size, but equally represented categories (dead vs alive) can be obtained by properly choosing the number of neighbors for the oversampling algorithm.

Results

The obtained mean subsets of relevant features and corresponding levels of accuracy (estimated as a mean after a cross-validation procedure of 50-folders) are presented in Table 2. The subset of relevant features is locked when (as previously explained) model accuracy reaches its maximum value. It is remarkable to note that, in any case, replacing the entire original set of 23 features by a much smaller subset with (at most) only 4 features (those identified as most relevant) produces the best model, which combines a reduction in computation load with maximum model accuracy.

In the cross validation code special attention was paid to avoid including synthetic data into the test stage. To this end the SMOTE balancing strategy was only applied to data belonging to training purposes folders.

Comparison among the predictors included in optimal subsets clearly shows that relevant features are different between women and men. Although gait and risk of fall associations in elderly people were examined in several studies (Bridenbaugh and Kressig, 2011; Howcroft et al., 2013; Marques et al., 2018; Meyer, 2010), stratified analyses by gender are still limited today (Thaler-Kall et al., 2015). This study addresses this deficiency and also adds gait performance and risk of mortality associations in elderly people.

The strongly different role played by feature22=age (important among the female population but irrelevant for the male sub-cohort) cannot be simply explained through differences in age data between the two sub-cohorts.

Indeed, Table 3 collects statistical parameters (mean and standard deviation) of age corresponding to subjects in both classes for both classification criteria and for both gender-stratified (shaded cells) sub-cohorts. Although there is always a slight mean age difference between the male and female sub-cohorts, this difference is so minor that why feature22=age plays such a very relevant role in the optimal features subset of the female population cannot be explained. Neither the distribution of the quantity of falls versus age nor the age at which death occurs (Fig.2) revealed any notable difference in age between the two gender-stratified sub-cohorts.

Discussion

Gait speed is a very important predictor, and very often used as the only feature (Meyer, 2010; Montero-Odasso et al., 2005), but model accuracy can be further increased if some other features (provided that they are properly chosen) are added to gait speed in train-and-test procedures. With 23 available features for a cohort of 261 elderly people, the main aim

of this work was to establish a ranking of features that allowed the extraction of an optimal subset to build a model with the minimum classification error in the prediction of both the risk of falling and mortality.
Indeed, any of the optimal feature subsets presented in Table 2 provides a model whose accuracy outperforms the traditional simple models where gait speed is the sole feature considered:

- Accuracy = 63.3% when predicting falls for the female sub-cohort
- Accuracy = 58.3% when predicting falls for the male sub-cohort
- Accuracy = 69.0% when predicting mortality for the female sub-cohort
- Accuracy = 53.4% when predicting mortality for the male sub-cohort

Note that accuracy values supplied in the preceding paragraph are not those consigned in Table 2 because feature23=gait velocity is not always identified as the first relevant feature in our feature selection algorithms.

The advisability of including sensor based kinematic features in the model is thus suggested. Regarding the identification of the most relevant features, the importance of a gender-stratified analysis becomes evident. Significant gender differences in the derived relevance subsets suggest that the fact of considering the strong gender component in walking metrics is quite important to adjusting a realistic predictor model. Although gender-specific analyses are scarce, they are expected to provide better results. There is a prior study of 890 participants that emphasized the relevance of examining the gender-specific associations between risk of falls and gait parameters measured with an electronic walkway (Thaler-Kall et al., 2015). However, contrary to the present work, the analyses in that study did not use gait performance to predict mortality and there is a lack of gait variability-related parameters (symmetry, regularity and total harmonic distortion) due to practical issues. In our proposal, inertial units overcome this limitation, making it possible to obtain gait variability-related parameters since there are no restrictions on the number of steps (Verghese et al., 2009). Our results draw the conclusion that both falls, as already shown (Marques et al., 2018; Meschial et al., 2014), and death happen differently when considering gender. In the literature it is stated that men reported poorer health and a greater number of underlying conditions than women (Meschial et al., 2014) and that men suffer from more comorbid conditions than women of the same age (Senden et al., 2012).
There are gender specific age related trends in physical performance measures (Taniguchi et al., 2016). Regarding gait, anthropometric characteristics makes men and women walking performance be different (Fragala et al., 2012; Musselman and Brouwer, 2005; Tseng et al., 2014). In particular, it is stated that elderly subjects showed difference in stride length with gender (Hollman et al., 2011; Samson et al., 2001). Here, similar disparities in gait parameters have been identified: elderly women showed significantly lower velocity, stride and step length values and higher cadence and stride duration values than elderly men did (Thaler-Kall et al., 2015). Therefore, higher fall risk is associated with women due to their longer stride times and higher variability (Hughes-Oliver et al., 2018). Moreover, women report more falls and experience more fall related injuries than men (Senden et al., 2012). The mechanisms behind this difference seem to be of multifactorial nature and further investigation would be of value (Stinchcombe et al., 2014). Only few studies within the literature evaluated gender differences in mortality prediction. They state that there is a clear evidence that different causes predicts death for men and women (Yates et al., 2017; Yuki et al., 2017) but none of them consider gait kinematics. Our study also states that fall risk and death are different between males and females and stratification is necessary.

Age (feature22) deserves special attention because it seems to be important only among the female population. This is probably due to a greater decline in physical performance measures for women as they age (Taniguchi et al., 2016). On one hand, gait speed decreases proportionally more with age in women than in men (Senden et al., 2012), although women maintain a higher cadence and smaller step length (Frimenko et al., 2015). On the other hand, the risk of falling in women has a greater influence of age (Campbell et al., 1989; Stinchcombe et al., 2014; Todd and Skelton, 2004), probably due to a higher prevalence of age-related risk factors among the female population (Chang and Do, 2015). In our female sub-cohort the feature subset composed of gait speed and age provides good predictions models for both risk of fall and mortality.
For the male sub-cohort, feature22=age is not present in the relevance ranking, and feature23=gait speed is preceded or even replaced by kinematic features (THD, HR, step regularity and RMS) for both risk of fall and mortality. The three spatial directions (anteroposterior, mediolateral and vertical) seem to be of similar importance, and thus, none of those directions can be considered the most significant. It is important to point out that although in the male group kinematic features appear in the set of relevant features, in the female subset, as it has been mentioned above, only gait speed and age are relevant.

Finally, we must emphasize that (a) it is vital to collect a large enough quantity of data to improve the models and (b) aging is a very complex process with multiple factors that are still incompletely understood. However, performing stratification by gender and adding different well-selected parameters related to functional capacity seem to be critical for improving the current predictive models of falls and mortality.

Conclusions and Implications

Our analysis revealed that when gender, age and biomechanical parameters are added to gait speed prediction of both, falls and mortality, is significantly improved. The outstanding accuracy value reported in Table 2 when predicting mortality for females is good proof of it. Many injuries have a strong gender component and consistent identification and understanding of such differences could help in the different processes of prevention, diagnosis and rehabilitation (Hardy et al., 2008). Further work is needed to understand the differences in disability because a deeper knowledge is essential to planning corrective and preventive actions (Hardy et al., 2008; Nakada et al., 2015). Globally, populations are rapidly ageing, leading to more older people, many of whom will experience mobility impairments. These studies would allow us to provide clinicians with tools to improve services for elderly people as well as preventive approaches and therapeutic interventions. Currently, many mobile phones and wearable devices already include simple gait parameters. As these devices improve and become more precise, they may include parameters such as those presented in this work. Thanks to this, a greater number of adverse events can be predicted, improving the quality of life of these people.

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Conflict of interest statement

All authors disclose any financial and personal relationships with other people or organisations that could inappropriately influence this work.

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Table 1: FEATURE NAMES AND NUMERICAL CODES

Table 2: FEATURES SUBSET AND CORRESPONDING MODEL ACCURACY

Table 3: AGE PARAMETERS UNDER GENDER STRATIFICATION

Figure 1. Balanced distribution regarding to falls for a) the entire cohort N261, b) the F158 female sub-cohort, and c) the M103 male sub-cohort. Imbalanced distribution regarding to mortality for d) the entire cohort N261, e) the F158 female sub-cohort, f) the M103 male sub-cohort.

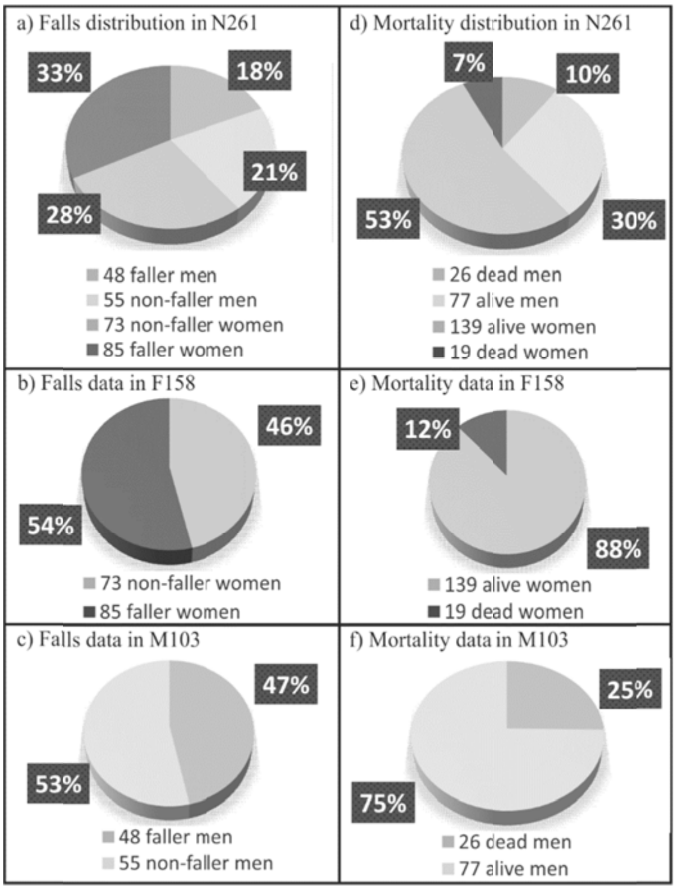
Figure 2. Distribution of amount of falls vs age for a) the F158 female sub-cohort, b) the M103 male sub-cohort. Histogram of death age for c) the F158 female sub-cohort, d) the M103 male sub-cohort.

Table 1

Feature name	Direction		
	AP	ML	V
Step Regularity	1	8	15
Stride Regularity	2	9	16
Symmetry Step/Stride	3	10	17
Approximate Entropy (AE)	4	11	18
Root Mean Square (RMS)	5	12	19
Harmonic Ratio (HR)	6	13	20
Total Harmonic Distorsion (THD)	7	14	21
Age	22		
Gait Velocity	23		
Gender *	24		

* Gender is used to distinguish between male and female sub-cohorts for gender stratified analyses. It is not used as feature.

Figure 1



a) Falls distribution in N261
33%
18%
21%
28%
48 faller men
55 non-faller men
73 non-faller women
85 faller women
d) Mortality distribution in N261
7%
10%
53%
30%
26 dead men
77 alive men
139 alive women
19 dead women
b) Falls data in F158
46%
54%
73 non-faller women
85 faller women
e) Mortality data in F158
12%
88%
139 alive women
19 dead women
c) Falls data in M103
47%
53%
48 faller men
55 non-faller men
f) Mortality data in M103
25%
75%
26 dead men
77 alive men

Table 2

Falls prediction best model for F158 female sub-cohort			
Relevant features subset	[23]	[23-22]	[23-22-8-17]
Model accuracy	63.3%	66.5%	70.9%
Model specificity	53.3%	60.5%	61.9%
Model sensitivity	72.9%	71.7%	74.1%
Falls prediction best model for M103 male sub-cohort			
Relevant features subset	[14]	[14-23]	[14-23-8-15]
Model accuracy	60.2%	65.0%	67.0%
Model specificity	76.4%	74.5%	72.7%
Model sensitivity	43.6%	56.2%	60.6%
Mortality* prediction best model for modified female sub-cohort			
Relevant features subset	[22]	[22-23]	
Model accuracy	69.7%	73.5%	
Model specificity	72.6%	72.7%	
Model sensitivity	68.3%	78.3%	
Mortality* prediction best model for modified male sub-cohort			
Relevant features subset	[6]	[6-19]	[6-19-14]
Model accuracy	65.1%	67.05%	69.0%
Model specificity	57.2%	63.8%	67.5%
Model sensitivity	72.6%	78.6%	85.3%

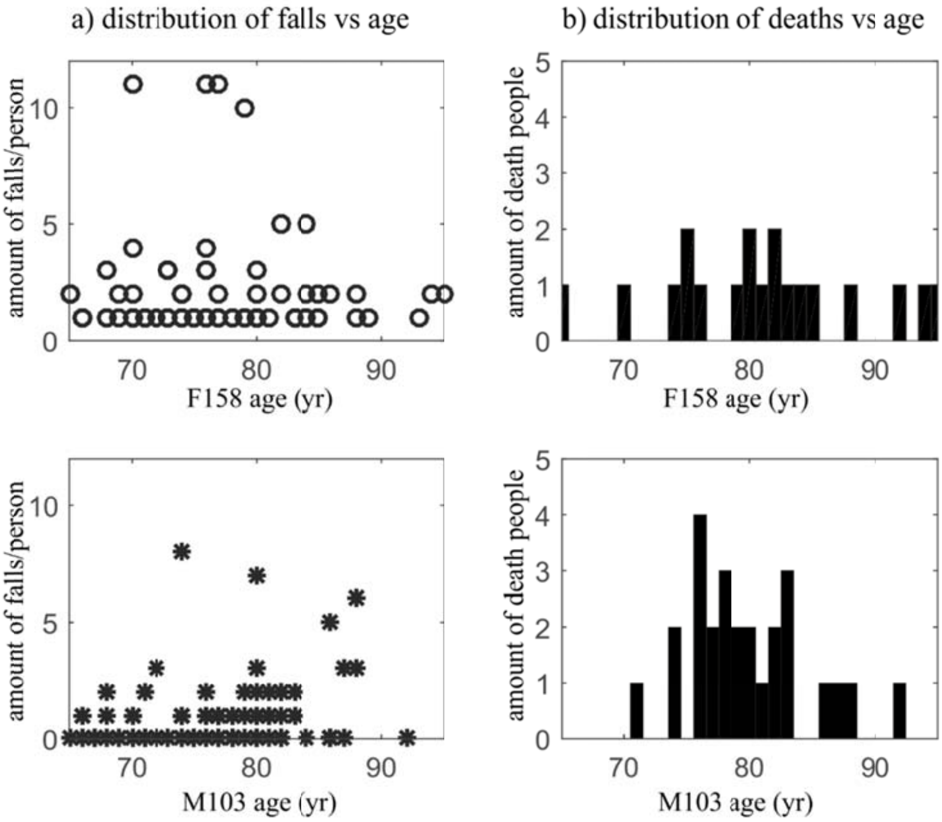
* The SMOTE algorithm was previously applied over training data when classifying by mortality.

Table 3

Population	Age (mean ± std)	Population	Age (mean ± std)
N261	75.7 ± 6.2	F158	75.1 ± 6.4
		M103	76.7 ± 6.0
Class 1=fallers # 133	77.1 ± 6.3	85 from F158	76.9 ± 6.7
		48 from M103	77.5 ± 5.4
Class 0=non-fallers # 128	74.3 ± 5.9	73 from F158	73.1 ± 5.2
		55 from M103	75.9 ± 6.4
Class 1=dead* # 45	80.4 ± 6.2	19 from F158	81.1 ± 7.8
		26 from M103	79.8 ± 4.8
Class 0=alive* # 216	74.8 ± 5.8	139 from F158	74.3 ± 5.7
		77 from M103	75.6 ± 6.0

* Data related to mortality come from the original unbalanced N261 cohort, before applying any SMOTE algorithm.

Figure 2



a) distribution of falls vs age
b) distribution of deaths vs age
amount of falls/person
amount of death people
F158 age (yr)
M103 age (yr)
0
5
10
1
2
3
4
70
80
90