A Highly Reliable Wrist-Worn Acceleration-Based Fall Detector

Majd SALEH*, Nawras GEORGI*, Manuel ABBAS* and Régine LE BOUQUIN JEANNÈS*
* Univ Rennes, Inserm, LTSI - UMR 1099, F-35000 Rennes, France
majd.saleh@univ-rennes1.fr nawras.georgi@univ-rennes1.fr
manuel.abbas@etudiant.univ-rennes1.fr regine.le-bouquin-jeannes@univ-rennes1.fr

***Abstract*—Automatic fall detection for the elderly is one of the most important health-care applications since it enables a rapid medical intervention preventing serious consequences of falls. Wrist-worn fall detectors represent one of the most convenient solutions. However, power consumption has a notable impact on the acceptability of such devices since it affects the size and weight of the required battery and the rate of replacing/recharging it. In this paper, an acceleration-based fall detection system is proposed for wrist-worn devices. It consists of two stages. The first one is a highly-sensitive low computational complexity algorithm to be embedded in the wearable device. When a potential fall is detected, raw data are transmitted to a remote server for accurate analysis in order to reduce the number of false alarms. The second stage algorithm is based on machine learning and applied to highly discriminant features. The latter are selected using powerful feature selection algorithms where the input is $12\ 000$ features extracted from each entry of a large activity dataset. The proposed system achieved an accuracy of 100% when evaluated on a 2400-file dataset. Moreover, the feasibility of the proposed system has been validated in real world conditions where it has been realized and tested using a smart watch and a server.**

***Index Terms*—fall detection, machine learning, elderly health-care, wearable sensors, feature selection.**

I. Introduction

A notable demographic shift has been evaluated by the World Health Organization (WHO) [1] where the number of people older than 60 years is expected to exceed the number of children younger than 5 years by 2020. This problem leads to major challenges to the health systems in all countries worldwide [1]. In a related context, WHO also showed that an average of 100 000 falls that require medical intervention occur every day worldwide and, as expected, the majority of fatal falls occur with people older than 65 years [2]. Therefore, automatic fall detection for the elderly is one of the most important health-care applications since it enables a rapid medical intervention and thus prevents serious consequences of falls. Thanks to the new technology of microscopic devices, namely Micro-Electro-Mechanical Systems (MEMS), a multitude of small-size light-weight wearable fall detectors have been developed over the last two decades. These devices use MEMS-based accelerometers, gyroscopes, magnetometers and/or barometers to capture the activity of the user. Waist-mounted fall detectors have shown high performance levels in the last years. Even using only an accelerometer, highly-accurate low-complexity solutions have been proposed in the literature. For instance, in [3] local binary features have been proposed to discriminate between falls and Activities of Daily Living (ADLs). These features were used to train several types of classifiers. Thanks to the small size of feature space, an efficient implementation was proposed where the trained model was not required in the embedded algorithm but a table that contains all the possible feature/response pairs was embedded instead. This algorithm achieved an accuracy of 99.65% with extremely low computational complexity [3]. Recently, two machine learning-based algorithms for acceleration-based waist-mounted fall detectors have been proposed in [4], both achieving an accuracy greater than 99.9% when evaluated on a large open dataset. This superior accuracy has been satisfied with quite low computational complexity which enables a fall detector to work for years with a 1000 mAh-battery. The main reasons underlying the high performance of waist-mounted fall detectors is that the waist is a good place to capture the activity of the user since it is close to the center of the body mass and the device could be tightly fixed in order to avoid oscillations. In spite of their perfect performance, waist devices could not easily accompany the elderly in any place, such as under shower, in bed, …etc. Therefore, alternative positions have been considered by researchers. Among the alternatives, the wrist is one of the most acceptable positions. Recently, Quadros *et al*. [5] have proposed an algorithm for wrist-worn fall detectors with an accuracy of 99.0%. Using an accelerometer, gyroscope and magnetometer, the orientation of the fall detector is estimated using Madgwick sensor fusion algorithm [6]. The extracted features are based on Euler angles that represent the orientation of the fall detector with respect to the Earth frame and the rest of features are extracted from vertical acceleration, velocity and displacement that also require estimating the orientation of the device. The classifier that shows the aforementioned result is k-NN. Despite the impressive accuracy of this algorithm, its complexity could considerably limit the battery life of a wearable fall detector. The complexity includes: 1) the hardware complexity due to the need for three sensors, 2) the need for fusion algorithm and 3) the complexity of the classifier where making a decision using a k-NN classifier requires calculating the distances between the extracted features vector and all the stored training vectors [4].

Power consumption of a wearable fall detector has a considerable impact on its acceptability for the following reasons: 1) the need for replacing/recharging the battery decreases with lower power consumption and 2) using small batteries enables producing small-size light-weight fall detectors. In order to minimize the power consumption, two factors are to be considered: (i) the computational complexity of the

978-9-0827-9703-9/19/$31.00 ©2019 IEEE

embedded algorithm should be low and (ii) since the power consumption of accelerometers is very low (few μAh) especially in comparison with gyroscopes [7], acceleration-based solutions are to be preferred. To this end, the objective of the current work is to investigate the feasibility of detecting falls using only an accelerometer in a wrist-worn device. The strategy proposed to tackle the aforementioned problem is to describe acceleration signals of falls and ADLs using a large number of features and then to apply a variety of feature selection methods to discover the most discriminant features. In order to decrease the computational load on the wearable device, feature extraction will be executed on a remote server only when a potential fall is detected by the wearable device as will be explained later.

Feature selection methods could be divided into filters, wrappers and embedded methods [8]. Wrappers and embedded methods employ a predictor to select the features while filters select features without optimizing the performance of a predictor [8]. The difference between wrappers and embedded methods is that the former use the predictor as a black box while in the latter, feature selection is involved in the training process. In this paper, the considered wrappers are: feature ranking based on individual feature performance using a logistic regression classifier, Sequential Forward Selection (SFS) [9] and Sequential Backward Floating Selection (SBFS) [10]. Note that the considered criterion to be maximized in both SFS and SBFS is the classification accuracy of a linear SVM classifier evaluated using 10-fold cross validation. The considered embedded methods are: Support Vector Machine based on Recursive Feature Elimination (SVM-RFE) [11], stepwise multi-linear regression, random forest and Neighborhood Component Feature Selection (NCFS) [12]. The considered filters are: feature ranking based on correlation coefficients, feature ranking using Fisher ratio and the minimum Redundancy Maximal Relevance method (mRMR) [13].

In the next section, we explain the challenges of detecting falls using acceleration-based wrist-worn devices before explaining the proposed methodology in Section III. Experimental results are described in Section IV before giving conclusion in Section V.

II. Challenges with acceleration-based fall detection using wrist-worn devices

Capacitive MEMS accelerometers are widely used in the context of fall detection thanks to their low cost, small size, light weight and low power consumption. Moreover, they can measure static accelerations contrary to the AC accelerometers like e.g. piezoelectric ones. For these reasons, the focus in this work is on capacitive MEMS accelerometers.

The measured tri-axial acceleration $\boldsymbol{a}$ in the sensor frame represents a vector combination of the dynamic acceleration $\boldsymbol{a}'$ caused by the body movement and the gravity acceleration $\boldsymbol{g}$ i.e. $\boldsymbol{a} = \boldsymbol{a}' + \boldsymbol{g}$. Theoretically, the measured acceleration represents the center of a unit sphere (the radius is one gravity unit) while the dynamic acceleration could be any point on the surface of this sphere. Figure 1.a illustrates the sensor coordinate frame while Figure 1.b illustrates an example of the aforementioned ambiguity. Separating $\boldsymbol{a}'$ and $\boldsymbol{g}$ could be quite useful for fall detection because each of them

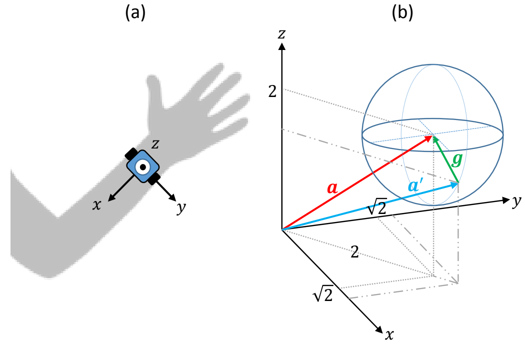

Fig. 1. A wrist-worn fall detector: a) the senor coordinate frame, b) an example illustrating the relationship between the measured, dynamic and gravity accelerations

could carry important indicators for falls. However, it is a demanding task as it requires a gyroscope and a sensor fusion algorithm like in [5]. On the other hand, working directly with the measured acceleration is a challenge because of the ambiguity discussed above. So, our objective is to use only the measured acceleration, $\boldsymbol{a}$, in order to discover features that can discriminate between falls and ADLs.

III. Methodology

A. Motivation

The presence of a high acceleration peak followed by inactivity is a strong indicator to detect falls [3]. However, it is not sufficient to avoid false alarms. For instance, laying down on a bed could easily satisfy the aforementioned situation. Therefore, sophisticated features should be extracted from acceleration signals in order to achieve an accurate solution. Studies on time series analysis in different application fields generally result in thousands of useful features. For a challenging problem like acceleration-based fall detection for wrist-worn devices, investigating the feasibility of employing these features is attractive. Thanks to the recent MATLAB tool, *hctsa* [14], [15], an automatic massive feature extraction could be applied to any time series. More than 7.700 time series features that encapsulate several decades of research in feature extraction could be employed. In our strategy, both of the last massive-feature-based solution and the simple low-cost criteria mentioned above are exploited.

B. The proposed fall detection algorithm

The activity of the user is captured using a 3-axial accelerometer built in the wrist-worn device. In order to analyze the acceleration signal during a sufficient period, the latter is buffered in a 3-second sliding window. More precisely, given that $\boldsymbol{a} = [a_x\ a_y\ a_z]$ denotes the acceleration, a_x and $\|\boldsymbol{a}\| = \sqrt{a_x^2 + a_y^2 + a_z^2}$ are buffered in the 3-second window $\boldsymbol{A} \in \mathbb{R}^{2\times 3f_s}$ where f_s denotes the sampling frequency. We only consider a_x and $\|\boldsymbol{a}\|$ since these signals are not affected when the device rotates around the wrist, recalling that a_x corresponds with the axis of the arm as shown in Figure 1.a.

The choice of the sliding window length is based on the time structure of falls. Indeed, falls consist of three phases namely pre-fall, critical and post-fall phases [16] as illustrated in Figure 2 where we represent the acceleration of a forward

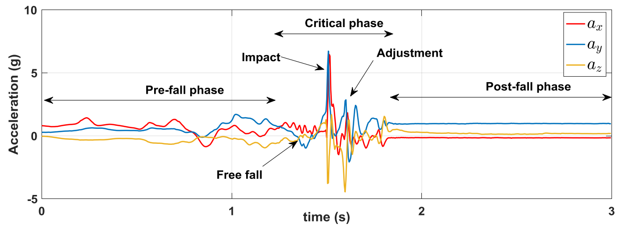

Fig. 2. Major phases of falls illustrated by 3-axial acceleration. Example of a forward fall caused by a stumble while walking.

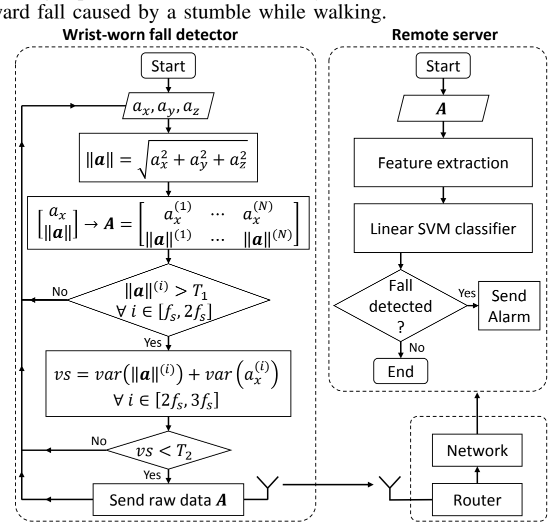

Fig. 3. Flowchart of the proposed fall detection system

fall caused by a stumble while walking. The critical phase includes a free fall followed by an impact when the body hits the ground and then an adjustment until the body takes its final position. Thus, at some instant of activity monitoring using overlapped windows, the sliding window captures all of the three phases of fall.

The proposed strategy is to detect falls in two stages as shown in Figure 3. The first one is a threshold-based algorithm to be embedded in the wearable device. This algorithm is designed to satisfy two objectives: 1) low computational cost in order to minimize the power consumption of the wearable device and 2) highly *sensitive* fall detection. When a fall is detected using this algorithm, the buffered acceleration $\boldsymbol{A}$ is sent to a remote server that performs machine learning-based fall detection where the objective is to minimize the number of false alarms. Both stages are discussed hereafter.

The embedded algorithm: as illustrated in Figure 3, $\|\boldsymbol{a}\|^{(i)} \forall i \in [f_s, 2f_s]$ is compared with a predefined threshold T_1 in order to detect the presence of an impact. If an impact is detected, the signal in the post-fall phase is inspected in order to detect inactivity. Particularly, the sum of variance of $\|\boldsymbol{a}\|^{(i)}$ and $a_x^{(i)}$ $\forall i \in [2f_s, 3f_s]$ is compared with a predefined threshold T_2. If inactivity is detected, the buffered acceleration $\boldsymbol{A}$ is sent to a remote server for further analysis.

The machine learning-based algorithm: in order to minimize the number of false alarms, features of higher discriminant power are required. Such features are to be extracted from $\boldsymbol{A}$ on the remote server. The question is: what are those features to be used in the machine learning-based algorithm? The proposed strategy is to perform a massive feature extraction using *hctsa* as introduced in III-A and then to select the smallest set of features that satisfy the maximum attainable accuracy. To implement the aforementioned strategy, we recorded 2400 activity signals from 7 subjects. These activities covered a variety of ADLs and simulated falls (further details on the dataset are explained in Section IV). From each activity signal, 12 000 features were separately extracted from a_x and $\|\boldsymbol{a}\|$. Let $\boldsymbol{B} \in \mathbb{R}^{2400 \times 12000}$ denotes the set of all the extracted features. Using 10-fold cross validation, the input of a feature selection algorithm is a subset $\boldsymbol{B}_i' \subset \boldsymbol{B}\ \forall i \in \{1, \ldots, 10\}$ where the dimensions of $\boldsymbol{B}_i'$ are 2160×12000. For comprehensive feature selection analysis, 10 methods have been considered including embedded methods, wrappers and filters as mentioned in Section I. The minimum set of selected features that satisfy 100% of accuracy has been chosen for the machine learning-based algorithm. When the server receives $\boldsymbol{A}$, it extracts the pre-defined set of most relevant features. These features represent the input of a trained linear SVM classifier. When the latter detects a fall, an alarm is sent to an authorized party as shown in Figure 3.

The performance of the considered feature selection algorithms, the predictive power of the extracted features and the performance of the proposed algorithm in a real world application are explored in the next section.

IV. Experiments

For training and performance evaluation, 7 young adults (4 males and 3 females) were asked to perform 19 types of ADLs and to simulate 35 types of falls. These activities were recorded using a wrist-worn data-logger equipped with a 3-axial accelerometer. The latter is a DC capacitive MEMS accelerometer. Its measurement range is ± 8 g and the sampling frequency is $f_s = 238$ Hz. Raw acceleration data were segmented into 2400 files (608 falls and 1792 ADLs). The considered performance criteria are accuracy, specificity and sensitivity [3], [4]. Note that the specificity is inversely proportional to the false alarm rate.

A. Analyzing the classification performance with a small set of features

In order to show the discriminant power of a small set of features, the top ranked three features selected using the SVM-RFE method are discussed in detail. The features, denoted as $F1$, $F2$ and $F3$, are extracted from a_x. Figure 4 shows how these features are extracted where an example of a backward fall occurred while walking and caused by a slip is considered. Feature $F1$ represents the discrepancy between the uniform distribution fitted to a_x and the kernel-smoothed distribution of the signal a_x denoted as $\hat{f}_h(u)$ where h represents the bandwidth of the scaled normal kernel used for smoothing. This discrepancy is measured as the distance between the left edge of the uniform PDF and the $\operatorname{argmax}_u \hat{f}(u)$ as illustrated in Figure 4.a. Features $F2$ and $F3$ are extracted from the standardized acceleration $\tilde{a}_x$. In order to extract the feature $F2$, the 3-second sliding window is divided into 5 sub-windows. The local sample entropy of $\tilde{a}_x$ is calculated for each sub-window resulting in a vector $\boldsymbol{s} = [s_1\ s_2\ s_3\ s_4\ s_5]$. Now, feature $F2$ is calculated as the standard deviation of $\boldsymbol{s}$ as illustrated in Figure 4.b. Thus, $F2$ is a measure of stationarity of a_x. In

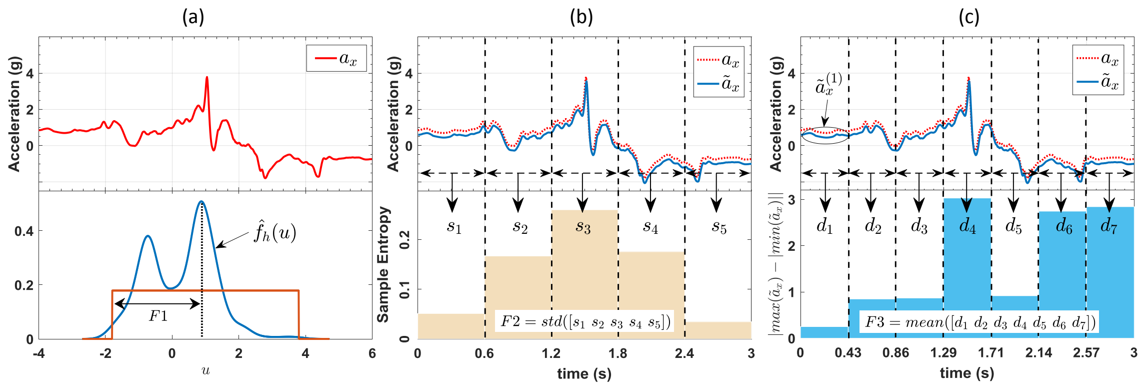

Fig. 4. How to calculate the top 3 features selected using SVM-RFE

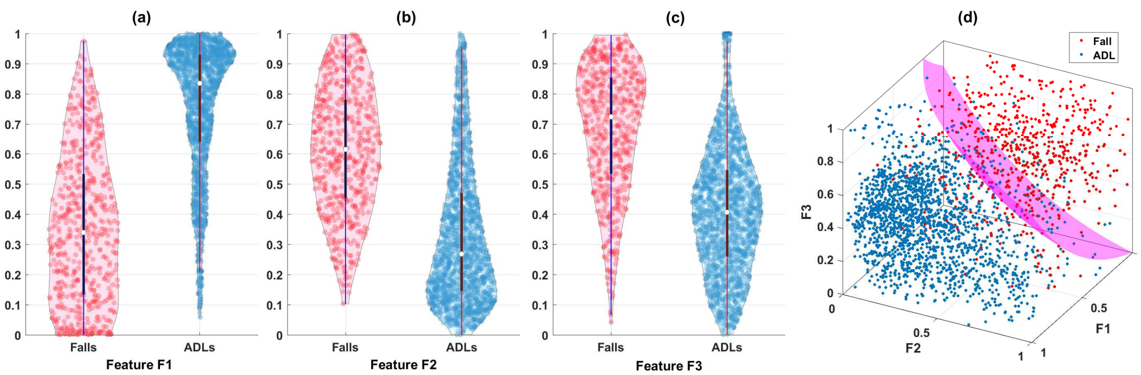

Fig. 5. The discriminative power of the top three features selected using SVM-RFE. Violin plots of features $F1$, $F2$ and $F3$ are illustrated in (a),(b) and (c), respectively. Sub-figure (d) illustrates a 3D representation of the falls and ADLs as well as the separating hyperplane achieved by a quadratic SVM.

a similar manner, $F3$ is extracted by dividing the 3-second sliding window into 7 sub-windows and calculating the local features $d_i = |\max(\tilde{a}_x^{(i)}) - |\min(\tilde{a}_x^{(i)})||$, $\forall i \in \{1, 2, \ldots, 7\}$, as illustrated in Figure 4.c. Thus, $F3$ reflects the variation of local maxima and minima across a_x. The individual discrimination performance of features $F1$, $F2$ and $F3$ is illustrated in Figures 5.a,b and c, respectively where violin plots show the distribution of the aforementioned features when extracted from falls and ADLs. From these violins, it is clear that none of these features is sufficient to discriminate between falls and ADLs. However, when considering a combination of these features, a quadratic-kernel-based SVM is able to separate the two classes with an accuracy of 92.35% as illustrated in Figure 5.d. More precisely, a 10-fold cross validation is applied to evaluate the performance of the aforementioned SVM classifier. The resulting accuracy, sensitivity and specificity are $92.35\%, 96.25\%$ and 80.78%, respectively. A linear SVM shows comparable results i.e. $91.58\%, 95.31\%$ and 80.56% of accuracy, sensitivity and specificity, respectively, as shown in Table I. These results show that higher dimensional features are needed basically to improve the specificity.

B. Analyzing the classification performance as a function of the number of selected features

The performance of the 10 feature selection algorithms considered in this paper is evaluated as a function of the number of selected features as illustrated in Figure 6. For each method, the number of selected features varies from 1 to $\min(300, sizeof(S_i))$ where S_i is the total number of the selected features using the i-th method. A 10-fold cross-validated linear SVM classifier is used to evaluate the performance of the selected features. Figure 6 shows that embedded methods display superior performance in comparison with wrappers and filters. Particularly, SVM-RFE presents the best result achieving a classification accuracy of 100% using the top 121 features, recall that the total number of extracted features is 12 000. The other methods show lower quality especially in terms of specificity as shown in Figure 6.

The top 121 features selected using SVM-RFE are based on entropy and mutual information, correlation, stationarity analysis, model fitting and spectral analysis. Explaining these features in detail is out of the scope of this paper. The last result satisfies the objective of this work where the problem of acceleration-based fall detection using wrist-worn devices is solved with 100% accuracy. It is also clear from Figure 6 that a trade-off between the classification accuracy and the number of selected features could be controlled in order to reduce the complexity of extracting features. Table I shows some interesting levels of the performance of top features selected using SVM-RFE. For instance, using the top 30 features, all performance criteria exceed 98%. However, this accuracy/complexity trade-off is not necessary as feature extraction is executed on a remote server which is able to calculate the 121 features rapidly.

C. Proof of Concept

The proposed first-stage fall detection algorithm was implemented in Java using Android Studio IDE and embedded

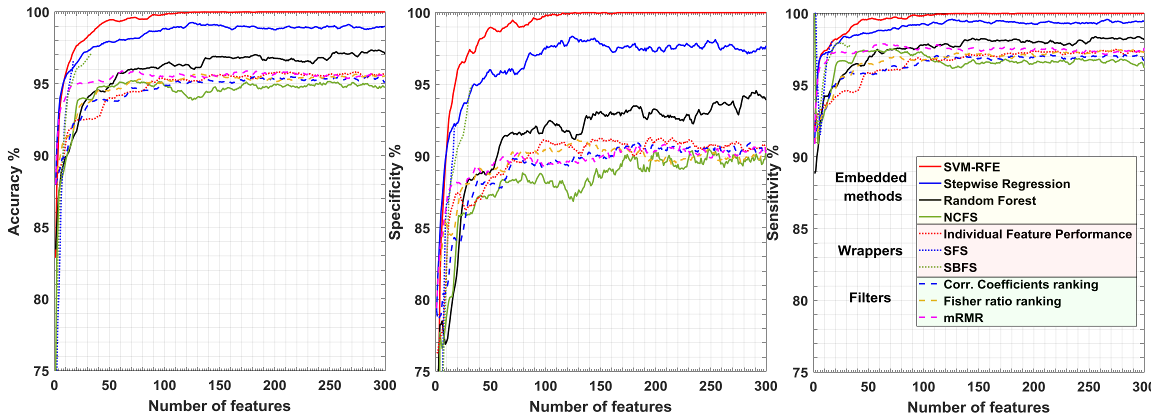

Fig. 6. Classification accuracy, specificity and sensitivity vs. the number of selected features. A comparative study between 10 feature selection methods

TABLE I
PERFORMANCE OF A LINEAR SVM CLASSIFIER APPLIED TO THE TOP x FEATURES SELECTED USING SVM-RFE

$x \rightarrow$	3	10	20	30	40	50	121
Accuracy %	91.58	95.75	97.71	98.42	98.83	99.50	**100**
Sensitivity %	95.31	97.32	98.27	98.55	99.10	99.67	**100**
Specificity %	80.56	91.10	96.05	98.02	98.02	99.01	**100**

in Huawei Watch 2. It is a smart-watch running Wear OS, a modified version of Android OS for wearable. The algorithm used the IMU which is a LSM6DS3 where the acceleration range is set to ± 8 g and the sampling frequency is 53 Hz. The proposed second-stage fall detection algorithm was implemented in MATLAB and installed on a server running a 64-bit Linux Debian Jessie 8 operating system on an Intel Xeon Processor 2.1 GHz and 16 GBytes of RAM. The system was tested by one subject where 5 types of ADLs i.e. walking, sitting down, standing up, laying down and rising up were performed and 4 falls in different directions were simulated. All falls were detected while no false alarm was generated. This validates the perfect accuracy of the proposed solution.

V. CONCLUSION AND FUTURE WORK

In this paper, the feasibility of detecting falls using a wrist-worn device that acquires the users' activities with only an accelerometer has been investigated. The problem of finding a set of features that can accurately discriminate between falls and ADLs has been tackled. Starting from a dataset of 2400 files, 12 000 features have been extracted from each file. They have been used as an input for a multitude of feature selection algorithms. SVM-RFE succeeded to reduce the number of features to 121 while keeping the best accuracy. The proposed fall detection system consists of two stages. The first represents a low complexity highly-sensitive algorithm to be embedded in the wearable device. When this algorithm detects a fall, it sends raw data to a remote server for further accurate analysis. Particularly, the 121 more discriminant features are extracted and supplied to a trained SVM classifier that predicts the class of the activity. The proposed system achieved an accuracy of 100% and its performance has also been validated in real world conditions. Currently, the system subjects to a long-term test where the objectives are to evaluate the average power consumption of the embedded algorithm and to evaluate the average number of events per day where accurate analysis is required by the server. In a future work, the feasibility of tackling the same problem using low complexity features will be investigated in order to develop a standalone fall detector.

ACKNOWLEDGMENT

This publication is supported by the European Union through the European Regional Development Fund (ERDF), the Ministry of Higher Education and Research, the French region of Brittany and Rennes Métropole.

REFERENCES

[1] World Health Organization (WHO). Ageing and health, (feb. 2018) https://www.who.int/news-room/fact-sheets/detail/ageing-and-health.

[2] World Health Organization (WHO). Falls, (jan. 2018) https://www.who.int/news-room/fact-sheets/detail/falls.

[3] M. Saleh and R. Le Bouquin Jeannès. An efficient machine learning-based fall detection algorithm using local binary features. In *EUSIPCO*, Rome, Italy, Sept. 3-7 2018.

[4] M. Saleh and R. Le Bouquin Jeannès. Elderly fall detection using wearable sensors: A low cost highly accurate algorithm. *IEEE Sensors Journal*, 19(8):3156–3164, 2019.

[5] T. Quadros, A. E. Lazzaretti, and F. K. Schneider. A movement decomposition and machine learning-based fall detection system using wrist wearable device. *IEEE Sensors Journal*, 18(12):5082 – 5089, 2018.

[6] S.O.H. Madgwick, A.J.L. Harrison, and R. Vaidyanathan. Estimation of IMU and MARG orientation using a gradient descent algorithm. In *IEEE ICORR*, Zurich, Switzerland, 29 June-1 July 2011.

[7] Q. Liu, J. Williamson, K. Li, W. Mohrman, Q. Lv, R.P. Dick, and L. Shang. Gazelle: Energy-efficient wearable analysis for running. *IEEE Transactions on Mobile Computing*, 16(9):2531 – 2544, 2017.

[8] I. Guyon, S. Gunn, M. Nikravesh, and L. A. Zadeh. *Feature Extraction-Foundations and Applications*. Springer-Verlag Berlin Heidelberg, 1 edition, 2006.

[9] A.W. Whitney. A direct method of nonparametric measurement selection. *IEEE Transactions on Computers*, C-20(9):1100–1103, 1971.

[10] P. Pudil, J. Novovicova, and J. Kittler. Floating search methods in feature selection. *Pattern Recognition Letters*, 15(11):1119–1125, 1994.

[11] I. Guyon, J. Weston, S. Barnhill, and V. Vapnik. Gene selection for cancer classification using support vector machines. *Machine Learning*, 46(1-3):389–422, 2002.

[12] W. Yang, K. Wang, and W. Zuo. Neighborhood component feature selection for high-dimensional data. *Journal of Computers*, 7(1):161–168, 2012.

[13] H. Peng, F. Long, and C. Ding. Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27(8):1226 – 1238, 2005.

[14] B.D. Fulcher and N.S. Jones. hctsa: A computational framework for automated time-series phenotyping using massive feature extraction. *Cell Systems*, 5(5):527–531, 2017.

[15] B.D. Fulcher, M.A. Little, and N.S. Jones. Highly comparative time-series analysis: the empirical structure of time series and their methods. *Journal of the Royal Society Interface*, 10(83), 2013.

[16] N. Noury, P. Rumeau, A.K. Bourcke, G. Olaighin, and J.E. Lundy. A proposal for the classification and evaluation of fall detectors. *IRBM*, 29(6):340–349, 2008.