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FALL DETECTOR USING DISCRETE WAVELET DECOMPOSITION AND SVM CLASSIFIER

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Abstract

This paper presents the design process and the results of a novel fall detector designed and constructed at the Faculty of Electronics, Military University of Technology. High sensitivity and low false alarm rates were achieved by using four independent sensors of varying physical quantities and sophisticated methods of signal processing and data mining. The manuscript discusses the study background, hardware development, alternative algorithms used for the sensor data processing and fusion for identification of the most efficient solution and the final results from testing the Android application on smartphone. The test was performed in four 6-h sessions (two sessions with female participants at the age of 28 years, one session with male participants aged 28 years and one involving a man at the age of 49 years) and showed correct detection of all 40 simulated falls with only three false alarms. Our results confirmed the sensitivity of the proposed algorithm to be 100% with a nominal false alarm rate (one false alarm per 8 h).

Keywords: fall detection, discrete wavelet transform, data fusion, support vector machine.

1. Introduction

Developments in the fields of medicine and technology have increased people's life expectancy, resulting in a growing number of old people in society [1, 2]. This population aging has consequences on the social, psychological, economic and political aspects of our life [3]. Hence, it is important to provide accurate medical care to the people most vulnerable to health problems, *i.e.*, the people aged more than 65 years [3, 4].

A significant problem of this age group is falls, which often lead to serious consequences. Slower reflexes, muscle stiffness and balance problems stem from physiological processes involved with age and are caused by changes in the human nervous system [3]. As a result, a risk of fall and, consequently, a probability of injury, increases significantly.

Falls are a significant problem for the elderly population [5]. Approximately 33% of the people over 65 years of age are vulnerable to falls, and this number increases with age [4, 6]. The world data report 391,000 deaths due to falls in 2002. Moreover, one out of four of these events took place in the high-income countries [4]. Over half of the fall incidents needed medical care and resulted in impairing mobility or even death [4–9].

Furthermore, falls may lead to mental changes, such as anxiety and depression, or may limit physical activity [3]. [10] defines this phenomenon as the post-fall syndrome. Quick detection of an uncontrolled fall facilitates delivery of timely and necessary medical assistance [11–13].

Falls may stem from a variety of causes. Most often they are triggered by environmental factors (31%), balance and walking disorders, fainting, epilepsy seizures (25%) or dizziness (13%) [14]. Other significant factors contributing to falls of old people include: single living,

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previous falls, decrease in mental acuity and fitness, chronic diseases, medicinal side effects, abnormalities in the walking pattern (such as unsure tiny steps made without raising the sole above the ground) and the condition of the cardiovascular and respiratory systems. Moreover, such conditions, as orthostatic hypotension (blood pressure fall) lead to fainting or balance disorder and, consequently, to an uncontrolled fall while changing the body position dynamically. Orthostatic hypotension is related to such a change of body position, which causes a sudden blood pressure fall of at least 20 mm Hg. Research shows that such a situation is observed in approximately 17–20% of the patients hospitalized and approximately 33% of the persons living single. The main consequences of falls are skull and brain injuries as well as long bone or great joint fractures. The percentage of fall-related deaths increases exponentially with age regardless of sex. It constitutes 70% of deaths among the persons over 75. Research indicates that the people who are unable to receive medical assistance within an hour of falling in their home die within the next six months.

These findings motivated the authors to create an ergonomic and reliable fall detector with an inbuilt function to send an alarm to a selected medical assistance center, family, friends or neighbors in the event of a fall. In contrast to existing solutions presented in [15], the designed detector integrates four sensors (accelerometer, gyroscope, magnetometer, pressure sensor) and its algorithm is based on the machine learning method. Independent sensors of four different physical quantities, as well as sophisticated methods of signal and data processing (presented in further sections) were used to ensure high reliability and minimize false alarms. The aim of this research was to design and construct a fall detector, as well as to develop a fall detection algorithm and an application which allows to communicate with the detector.

2. Hardware

The data source was a custom designed detector, as described in [11, 12]. The device combines four MEMS sensors, consisting of a pressure sensor and three tri-axial sensors (accelerometer, gyroscope and magnetometer), as shown in Fig. 1. The designed detector can handle ten axes of data – *i.e.*, it is a 10 DOF (*Degrees Of Freedom*) sensor.

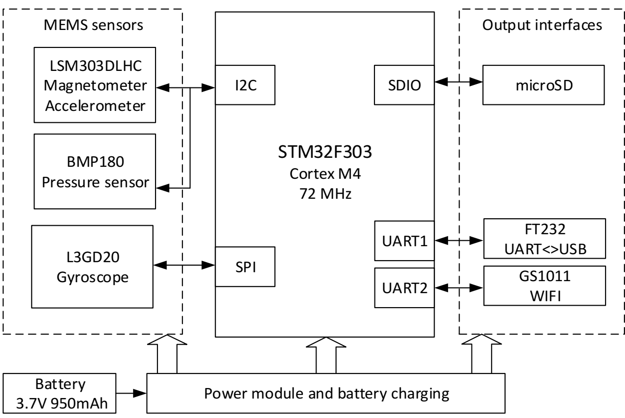

Fig. 1. A block diagram of the designed detector.

The detector hardware is based on a 32-bit microcontroller STM32F303 with CortexM4 core. The CPU processing speed is 72 MHz. Data transmission between the MEMS sensors and the microcontroller is through serial buses. An L3GD20 gyroscope is connected to the microcontroller through an SPI bus. Other two sensors, the LSM303DLHC (integrated

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accelerometer and magnetometer) and the BMP180 (pressure sensor) are connected through I^{2}C buses.

Using its sensors, the detector device can record data on a microSD card or transmit them in real time via Wi-Fi or USB interface, thereby operating as a virtual serial port.

A Li-Ion 950 mAh, 3.7 V battery keeps the system running up to six hours without recharging. Moreover, the device has an integrated battery charging module powered via the USB port. The device housing was manufactured using a 3D printer.

3. Preliminary research and algorithms optimization

3.1. Experimental setup

The fall detector is designed to be worn as a chest strap. Data are transmitted between the detector and a computer through a Wi-Fi network. The feature extraction and fall detection tasks are performed using a program coded in Matlab. The sensor signals are recorded at a frequency of 25 Hz. The processed and analyzed frame has the length of 100 samples, which corresponds to 4 sec of data registration. The measurement system scheme and a photograph of the designed detector are shown in Fig. 2.

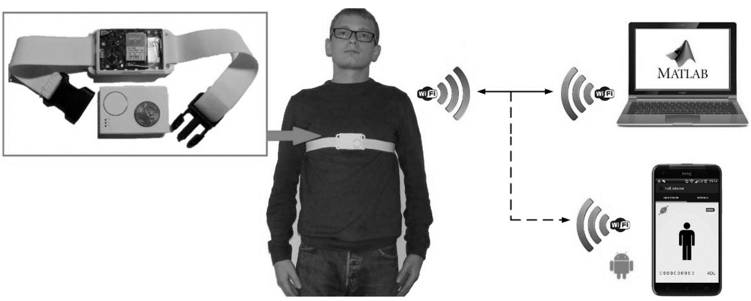

Fig. 2. The scheme of the measurement system.

The data collection program is written in Matlab. The graphical user interface (GUI) can be divided into five main sections, as shown in Fig. 3 (A, B, C, D and E). Section A controls the connection between the data acquisition application and the detector; the user can select and configure either a Wi-Fi or virtual serial port. Section B shows the classification result of the registered activity: FALL or ADL *(Activity Daily Living)*. Furthermore, the user can select and configure the fall detection algorithm by setting a threshold value of the number of falls in the classification buffer and/or by setting the classification buffer mask. The application also displays the detector battery voltage. Section C presents the view from a camera connected to the computer. Section D displays the real-time raw data received from all of the sensors of the detector. The last section contains information about the decision buffer. All of the detected fall events are registered in this area and saved in a log file.

3.2. Feature extraction and fall detection algorithm

From the pilot studies, we found that using the square root of the sum of the squares of the component data from each 3D sensor was much more advantageous for fall detection than using each component data separately. Therefore, the total sum of data from each 3D sensor was used as the input signal for the feature extraction block.

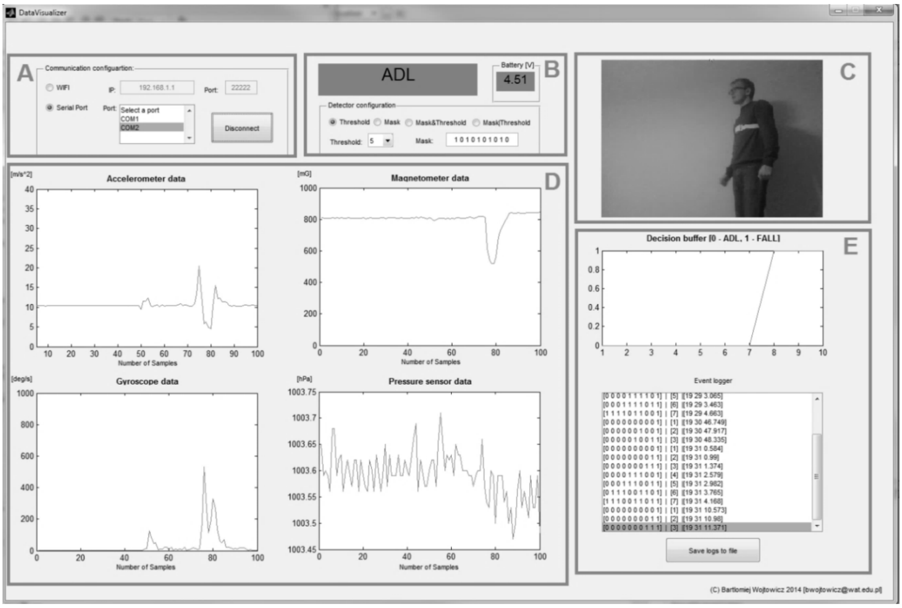

Fig. 3. The application for data acquisition from the detector.

Based on the previous work, the feature extraction was performed using the DWT (*Discrete Wavelet Transform*), while the data classification was performed using the linear SVM (*Support Vector Machine*) [16, 17]. In the iterative process used for all of the sensors, the wavelet, the number of decomposition levels and the number of descriptors for each decomposition level were chosen. The extracted features were defined as the maximum value of the wavelet transform detail coefficients. The number of maxima was determined individually for each level of transformation [13, 18].

The first stage of the study involved registration of 50 frames of the signals, half of which were various types of falls (*Fall*). The other half of the signals included *Activity Daily Living* (ADL). To verify the algorithm accuracy we tested a registration set of 25 falls and 40 ADL. At this stage of the study, including the training and testing processes, the fall event occurred approximately in half of the analyzed frames of 100 samples.

The block diagram of the feature extraction and the SVM training process is shown in Fig. 4a. The fall detection algorithm presented in Fig. 4b is configured in the same way as the SVM network in the training process. The designated descriptors go to the SVM responsible for proper activity classification (*Fall* or ADL).

3.3. Individual sensor results

Table 1 presents the configuration parameters of the feature extraction block for each sensor, as determined from the iterative optimization process. These parameters represent the best results obtained by manipulating the standard types of wavelet and the maximum number of detail coefficient modules. The training and testing sets were 100 samples long and the falls occurred in half of the analyzed frames. The sensor names were abbreviated as follows: ACC – accelerometer, GYR – gyroscope, MAG – magnetometer, PRESS – pressure sensor.

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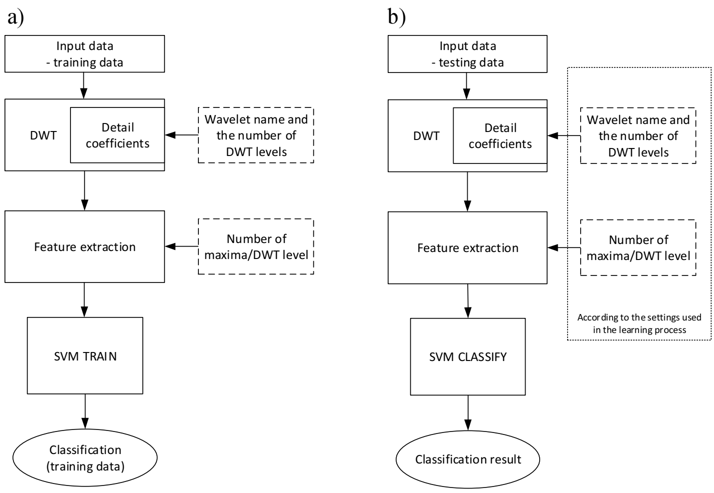

Fig. 4. a) The SVM training process and feature extraction; b) a block diagram of the uncontrolled fall detection.

Table 1. The designated configuration parameters of the feature extraction process.

Sensor	Wavelet name	The number of DWT levels	Number of maxima/DWT level [p_1 p_2 p_3 p_4 p_5]
ACC	coif3	5	[0 0 5 4 1]
GYR	sym2	5	[5 0 8 0 1]
MAG	db4	5	[0 2 4 0 1]
PRESS	db4	5	[0 4 1 1 1]

where p_i is the level of decomposition

Table 2 presents the results from the classification mechanisms for the data from each sensor.

Table 2. Classification results on the basis of the data from available sensors.

Data	FALL/ADL	Correct classification			
		ACC	GYR	MAG	PRESS
Training	ADL	25/25	25/25	25/25	25/25
	FALL	25/25	25/25	20/25	23/25
Testing	ADL	40/40	40/40	38/40	38/40
	FALL	25/25	24/25	19/25	22/25

The next step of the study involved determination of an impact of the fall event moment in the analyzed frame on effectiveness of the classification process. The process signal frame selection is depicted in Fig. 5. The obtained results are presented in Table 3.

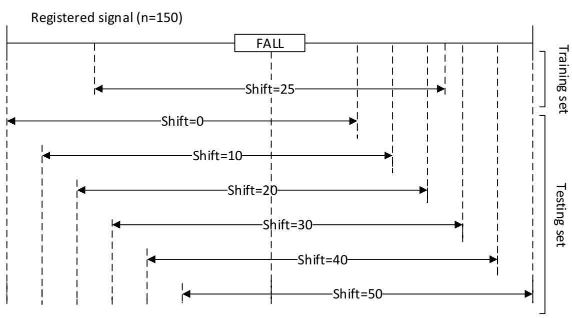

Fig. 5. The illustration of selection of six signal frames with different moments of fall events.

Table 3. The results of classification, taking into account different fall positions in the analyzed frame for sensors.

Sensor	Shift	0	10	20	30	40	50
Accelerometer	Incorrect FALL classification (Total=6*50)	3	7	0	0	0	5
	Incorrect ADL classification (Total=6*65)	0	2	0	1	1	0
Gyroscope	Incorrect FALL classification (Total=6*50)	4	1	2	1	1	1
	Incorrect ADL classification (Total=6*65)	0	1	0	2	1	2
Magnetometer	Incorrect FALL classification (Total=6*50)	16	16	17	16	16	17
	Incorrect ADL classification (Total=6*65)	2	5	4	2	3	3
Pressure sensor	Incorrect FALL classification (Total=6*50)	43	45	35	12	3	11
	Incorrect ADL classification (Total=6*65)	2	7	6	5	8	7

The classification performances were examined on the basis of three indices:

a) *Sensitivity* – (*SE*) – corresponds to the ratio of correctly detected falls *TP* (*True Positive*) to the total number of falls (the sum of correctly detected falls *TP* and undetected falls *FN* – *False Negative*):

$$SE = \frac{TP}{TP + FN}. \tag{1}$$

b) *Specificity* – (*SP*) – corresponds to the ratio of correctly detected ADL *TN* (*True Negative*) to the total number of ADL (the sum of correctly detected ADL *TN* and false fall alarms *FP* – *False Positive*):

$$SP = \frac{TN}{TN + FP}. \tag{2}$$

The probability of a false alarm can be calculated as $PFA = 1 - SP$.

c) *Total Error* – (*TE*) – corresponds to incorrect differentiation between falls and ADL:

$$TE = \frac{FP + FN}{TP + TN + FP + FN}. \tag{3}$$

The indices calculated based on the data from Table 3 are presented in Table 4.

Table 4. The measures of quality assessment of classifiers.

Sensor	*SE*	*SP*	*TE*
Accelerometer	0.950	0.990	0.028
Gyroscope	0.967	0.985	0.023
Magnetometer	0.673	0.951	0.170
Pressure sensor	0.503	0.910	0.267

The outcomes were the basis for presenting all of the sensors using the ROC curve (*Receiver Operating Characteristic*). It has been depicted in Fig. 6 with four triangles. It should be emphasized that the efficiency of the fall detection process was higher with an

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increased bend of the ROC curve toward the upper-left corner of the chart [19]. Additionally, the best results were obtained by using the gyroscope, the accelerometer, the magnetometer and the pressure sensor (allowing to determine relative changes in the height).

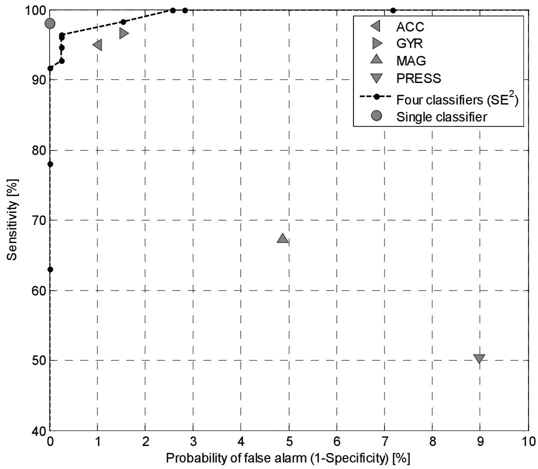

Fig. 6. The ROC curves for different system configurations.

3.4. Data fusion algorithm with four independent classifiers

After performing the tests to determine the performance of the SVM classifier for fall detection for each sensor, data fusion was performed to increase the efficacy and efficiency of the fall detector. Fig. 7a shows a solution based on four independent classifiers for each sensor when weighted mean was used to reach the final decision. Table 1 presents the feature extraction block parameters. Weighted mean was set on the basis of the binary decisions (D) developed by all of the available sensors, taking into account their weights (w), using the following equation:

$$WM = \frac{D_{ACC}w_{ACC} + D_{GYR}w_{GYR} + D_{MAG}w_{MAG} + D_{PRESS}w_{PRESS}}{w_{ACC} + w_{GYR} + w_{MAG} + w_{PRESS}}. \tag{4}$$

The final decision depends on weighted mean (WM) and the decision threshold value (TH). It is defined as:

$$\begin{cases} WM \le TH \rightarrow ADL \\ WM > TH \rightarrow FALL. \\ TH \in <0;1> \end{cases} \tag{5}$$

As mentioned earlier, the fall detection process was more efficient when the ROC curve was closer to the upper-left corner of the graph. The previous research presented in [13] confirms that the best results are obtained for the ROC curve determined using square of sensitivity (SE^2).

Using SE^2 significantly reduces the parameters of very small values. Thus, the differences between the importance of each sensor in the process of fall detection are more visible.

Figure 6 presents the ROC curve determined on the basis of the above-defined set of 690 test cases, where the threshold value TH changed from 0 to 1. For this curve, the characteristic of the sensitivity and the probability of false alarms as a function of the decision threshold TH value was designated (Fig. 8). The TH value is the key parameter of the proposed algorithm.

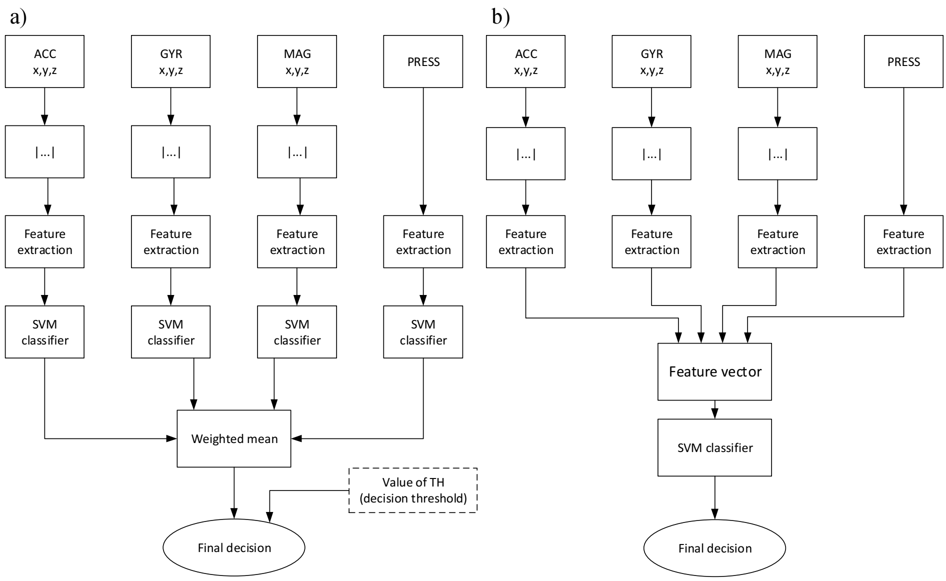

Fig. 7. The fall detector data fusion algorithm: a) with four independent classifiers; b) using a single classifier.

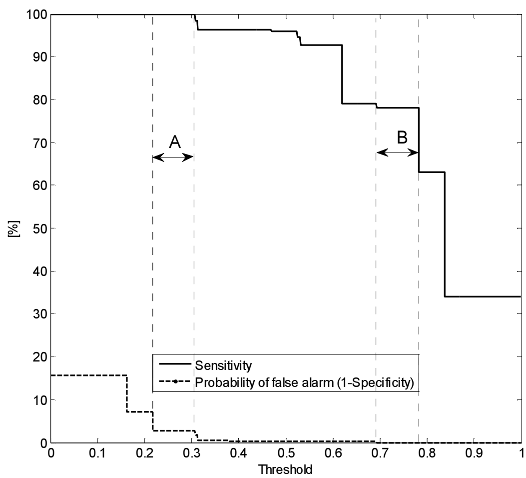

Fig. 8. The probability of correct fall detection and false alarms as a function of the decision threshold.

A low threshold value results in a very high sensitivity; however, the number of false alarms is not reduced to zero. A high threshold value allows to minimize the number of false alarms, but the sensitivity of fall detection is reduced by approximately 35%. In Fig. 8 two characteristic threshold value ranges have been marked:

– A – The system detects all fall events correctly; the number of false alarms is fractional.
– B – The system does not report false alarms; not all falls are detected correctly.

In terms of the developed solution, the choice of *TH* in the A range was most favorable. False alarms occurred with the probability of 2.82%.

Comparing the obtained results with the findings for each sensor working independently (presented in Section 3.3), the proposed data fusion algorithm based on weighted mean increases the efficiency of accurate fall detection up to 100%.

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As a result of the data fusion based on weighted mean, it was possible to enhance the classification performance. All falls were detected correctly and the number of false alarms was fractional. Furthermore, the proposed algorithm was not sensitive to the moment of fall event in the analyzed frame. Therefore, the probability of correct operation of the detector in real conditions was high.

3.5. Data fusion algorithm using a single classifier

The algorithm presented in the previous section involved high computational complexity, as the classification was performed using SVM for each sensor individually. In view of this drawback, we performed a study to search for an algorithm which involved lower computational complexity while maintaining all other properties of the previous system. Therefore, a fall detection algorithm based on a single linear SVM classifier was developed and implemented (Fig. 7b). It is a modification of the algorithm presented in [13].

As the first step, the algorithm accuracy was verified. The training and testing sets were selected in the same way, as described in Section 3.2. The results showed that 100% of the tested activities were classified correctly.

In the next step, an influence of the fall event moment in the analyzed frame was studied, as in Section 3.3. The classification results are summarized in Table 5. On the basis of our findings, the quality of the classifier was evaluated. We determined the sensitivity, specificity and total error values, which were SE = 98%, SP = 100%, TE = 0.9%, respectively.

Table 5. The results of the classification taking into account a different fall position in the analyzed frame.

SHIFT	0	10	20	30	40	50
Incorrect FALL classification (Total = 6*50)	3	1	1	0	0	1
Incorrect ADL classification (Total = 6*65)	0	0	0	0	0	0

On the basis of the results, we determined the classifier parameters and presented the developed algorithm in the field of ROC curves and compared them with the solutions presented in Sections 3.3 and 3.4. The developed algorithm is shown in Fig. 6 as the gray circle. As illustrated, the single classifier algorithm gave the best results.

3.6. Feature set reduction

The algorithm proposed in the previous section used 38 descriptors for training and testing. This number is the sum of all of the features determined for each sensor built in the fall detector. Considering the registered set of data (50 *Falls* and 65 ADL), the ratio of the number of input vectors to the number of features equals 1.3 for *Falls* and 1.7 for ADL. Furthermore, an excessive increase in the number of descriptors during the training and testing processes does not lead to enhanced accuracy of classification. This is because the set of attributes may include features with measurement noise. Therefore, for improving the system efficiency, a proper feature selection is essential, which was the main objective of the next phase of study.

Fisher Score was used for feature reduction. This method is one of the most intuitive ways to evaluate a single feature used in binary classification problems. Fig. 9 presents Fisher Score for each feature. The features associated with particular sensors are marked with different colors. The use of the Fisher Score decision threshold (TH_{FISHER}) allows omitting the features with values not exceeding a specified threshold. This study used TH_{FISHER} value between 0.1

and 0.9. Further increasing TH_{FISHER} (>0.9) might remove an influence of the sensors with lower discriminating ability.

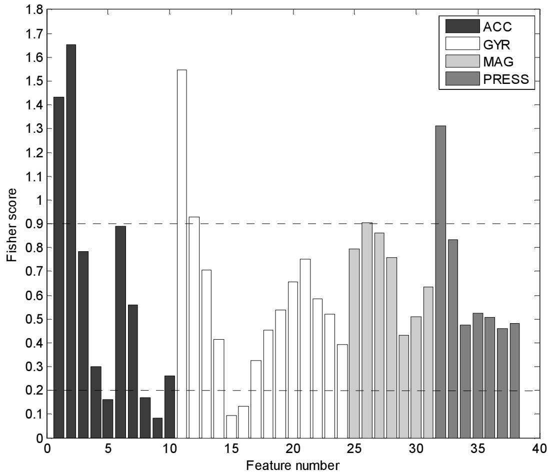

Fig. 9. Fisher Score determined on the basis of the full set of registered data (50 *Falls* and 65 *ADL*).

Selecting 0.2 or 0.9 as the Fisher Score threshold (TH_{FISHER}) seemed to be most favorable. The number of support vectors was nine and six, respectively, for the above settings. By reducing five features ($TH_{FISHER} = 0.2$), the sensitivity decreased by only 0.33% in comparison to the use of the full set of descriptors. In this case, the number of false alarms was still 0. Setting $TH_{FISHER} = 0.9$ caused degradation of the classifier sensitivity and specificity. However, the number of support vectors was reduced significantly – to six only.

Additionally, reducing the number of support vectors decreased also the upper bound of the classification error, defined as the ratio of the number of support vectors to the total number of training data minus one [20]:

$$P \le \frac{N_{SV}}{p-1} = \frac{6}{50+65-1} = \frac{6}{114} \Rightarrow P \le 5{,}3\%. \tag{6}$$

For this reason, to improve generalization of the SVM, the number of support vectors should be reduced, even at the expense of the number of correct classifications.

In Table 6, the classifier parameters obtained for different TH_{FISHER} threshold values have been summarized. These results were obtained for the full set of cases with different moments of fall events in the analyzed frame obtained according to the scheme shown in Fig. 5 (690 cases).

The PCA analysis was performed to obtain a fuller assessment of an impact of the removal of features (with a Fisher Score value less than a given threshold) on the class separability representing falls and ADL. On the basis of the PCA analysis, it can be concluded that setting $TH_{FISHER} = 0.9$ does not significantly deteriorate the separability of classes representing falls and ADL. As a result, the authors decided to set the threshold to this level, which significantly reduced computational complexity while providing the minimum value of the upper bound of the classification error (6).

The number of support vectors notably influences the efficiency of SVM [21]. Due to the relationship between the number of training sets and the number of support vectors, which directly affects the upper bound of the classification error, reduction of descriptors was made. Fisher Score was used as a selection criterion. Consequently, satisfactory results were

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obtained by reducing the number of descriptors from 38 to just 6, ensuring that the upper bound of the classification error in a set of new test data did not exceed 5.3%.

Table 6. The classifier parameters according to the TH_{FISHER} value.

Threshold TH_{FISHER}	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Number of support vectors of SVM	13	12	9	11	11	10	9	8	7	6
Number of features	38	36	33	32	29	23	16	14	9	6
SE [%]	97.3	98	97	97.3	97.3	96.3	93	94	91.7	95.7
PFA [%]	0	0	0	0	0.26	0.51	0	0.51	0.26	0.77
Upper estimate for error [%]	11.4	10.5	7.9	9.6	9.6	8.8	7.9	7.0	6.1	5.3

3.7. Mobile application

To verify correctness of the algorithm based on a single classifier and reduced feature set, a mobile application for Android system was developed. This Android system enabled real-time communication with the fall detector via Wi-Fi. The fall detection algorithm was coded in JAVA. The data received from the detector were processed by the mobile application. Subsequently, classification of the data based on a 100-sample long buffer was performed with a 10-sample step. The application allowed configuring optimal settings of the buffer mask and buffer threshold value, similar to the case of the application coded in Matlab. When detecting a fall, the application starts counting down (from 10 to 0), and to minimize the number of false alarms; it allows the user to cancel the triggered procedure.

The tests of the designed and implemented solution included testing of the system during continuous use. The test was carried out in four 6-h sessions: two sessions with the participation of women at the age of 28 years, one session with the participation of men aged 28 years and one involving a man at the age of 49 years. The test was designed taking into account activities which exceeded the requirements for such types of devices used by elderly people. Additionally, ten falls were simulated during each session.

The determined optimal application configuration parameters (TH = 3 AND MASK = [1 1]) resulted in satisfactory results. The detector detected all simulated falls (40 probes of different types), confirming 100%. sensitivity of the developed algorithm Moreover, the device presented a marginally low probability of false alarms at the frequency of one false alarm per 8 h.

4. Conclusion and future work

The presented study is a continuation of the studies described in [11–13]. This article presents design and construction of a fall detector. The implemented algorithm is based on wavelet decomposition as a feature generator, using the SVM as a classifier. This concept gave satisfactory results, improving the efficiency of fall detection in comparison with the solution proposed in [13].

The best detection capabilities of the designed algorithm were obtained by the gyroscope and the accelerometer, followed by the magnetometer and the pressure sensor. Additionally, it was found that the best detection capabilities and the lowest computational complexity were presented by the algorithm based on a single SVM classifier, which was implemented in the final solution.

Further work will aim at implementing the algorithm from the Android device into an independent microprocessor system equipped with a GSM module. Such a device may be an autonomous, low-energy fall detector, which does not require a smartphone. Furthermore, the authors will envisage testing of the designed device in a group of elderly people selected by physicians. Additionally, we plan to implement a pilot program to launch our fall detector to the medical services market.

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