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Discriminant Analysis in Bioradar-based Fall Events Classification

Lesya Anishchenko, Irina Alborova, and Maria Dremina
Remote Sensing Laboratory, Bauman Moscow State Technical University, Moscow, 105005, Russia
Email: anishchenko@rslab.ru

***Abstract*—This work presents the results of studies carried out to confirm the possibility of using bioradar for the fall detection. We used different types of discriminant analysis to classify movement patterns detected by the bioradar into 'fall' and 'not fall' events. Classifiers were tested on the experimental dataset recorded by continuous wave radar: BioRASCAN-4. It contains 338 records of various basic movements (including 51 fall records). For classification features of bioradar signals in time domain were used. The performance of the classifiers was evaluated calculating classification accuracy and Cohens kappa coefficient.**

***Index Terms*—Discriminant analysis, Doppler radar, fall detection, machine learning.**

I. Introduction

The elderly population of the world has been continuously increasing [1]. In Russia, more than 20 % of citizens have already celebrated their sixtieth birthday. The same is the situation in the majority of countries, which is a challenge for the present society [1]. The aging process is accompanied by degradation of many systems and organs of the body, which impairs the daily quality of life and gradually increases the risk of fall. The latter significantly affects morbidity and quality of life as well as health care costs among the aging population [2]. According to WHO "falls are the second leading cause of accidental or unintentional injury deaths worldwide"[3]. One of the factors influencing the severity of fall consequences in elderly is the amount of time spent lying on the floor or ground waiting for help. The most crucial are the situations after falling down when the elderly person is injured and cannot call for help. The less time is spent waiting for the help the more successful recovery and returning to the natural life rhythm are. Therefore, in recent years, more and more scientists have been paying their attention to development of effective fall detection system and methods.

There are many commercially available wearable devices for motion activity tracking and fall detection based on movement sensors (e.g., accelerometers and gyroscopes) [4], [5]. However, it should be noted that wearable devices are not always comfortable to use, due to the memory impairment the user might forget to put it on, which is quite common situation. Moreover, such devices have a significant false-positive rate.

Current approaches for remote fall detection are based on video cameras or depth sensors usage [6], [7]. However privacy issues do not allow to use such systems to watch over a bathroom zone, where the chance to fall is high [8]. Moreover, these methods are sensitive to lighting conditions and can be blocked by optically opaque obstacles such as walls and fabrics.

Doppler radars have also been studied as a possible fall detectors [9], [10], [11], [12]. However, the majority of authors analyze the radar signal in the frequency domain. In the present work, we propose the classifier, which uses features extracted from the bioradar signal in time domain, which simplify the processing algorithm greatly. This issue may be crucial while implementing the proposed technology on practice.

TABLE I
Technical characteristics of BioRASCAN-4

Parameter	Value
Number of frequencies	8
Operating frequency band, GHz	3.6 – 4.0
RF output, mW	<3
Gain constant, dB	20
Detecting signals band, Hz	0.03 – 10.0
Dynamic range of the detecting signals, dB	60
Size of antenna block, mm	370x150x150

II. Methods and Experiments

At present study a stepped frequency continuous wave bioradar (BioRASCAN–4) operating at 3.6 – 4.0 GHz frequency range was used. The radar was designed at Remote Sensing Laboratory, Bauman Moscow State Technical University [13]. Its technical characteristics are listed in Table I.

The bioradar is equipped with two co-located standard gain horn antennas adopted to generate and detect the electromagnetic signal.

The maximum power density radiated by the bioradar is equal to 1.36 μW/cm^2. Such a value satisfies the Russia safety standard for microwave emission, which is 25 μW/cm^2 in the frequency range of 3-300 GHz (for 24 hours exposure) [14].

The experiments were carried out at the Remote Sensing Laboratory to investigate the possibility of bioradar usage in fall detection. Three healthy volunteers participated in them. Each of them gave the informed consent prior to the experiments. The radar was positioned 3 m from the experimental scene. The scheme of the experiment is given in Fig. 1.

Each examinee was asked to perform different types of everyday movements such as: going in and out of the room, sitting on the chair and standing up from it, turning around and moving arms up and down. Moreover, examinees were

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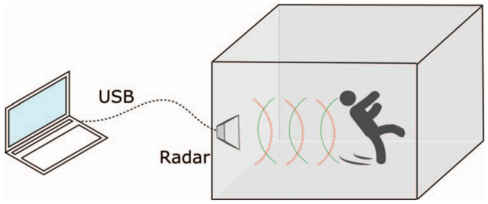

Fig. 1. The scheme the experiment.

TABLE II
MOVEMENT PATTERNS

Movement type		Number	
Going in and out of the room	All non-fall movements	52	287
Turning 180		52	
Turning 90 deg		35	
Arm movements		76	
Sitting on the chair and standing from it		42	
Standing up from the bed		30	
Falls		51	51
All types of movements		338	

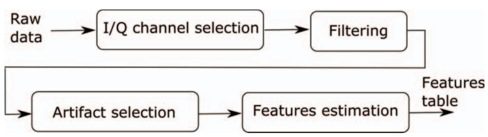

Fig. 2. Preprocessing algorithm scheme.

mimicking falls on a previously prepared floor covering to make the falling as save as possible.

Experimental data set contains 338 different movement patterns, 51 of which are “falls”, other 287 are “non-falls” (Table II).

III. DATA PROCESSING

The scheme summarizing the steps of the signal preprocessing is depicted in Fig. 2. Data preprocessing and classification were done utilizing MATLAB 2016b.

Each BRL record consists of 16 signals (8 operating frequencies, each of them has I and Q quadratures), which were recorded simultaneously. For movement pattern classification we used only data of the quadrature, which maximizes the energy.

The selected quadrature signal was filtered by a 7th order Butterworth filter with cutoff frequency of 0.3 Hz. As opposed to [11] in present work movement artifacts were automatically detected by the adaptive threshold algorithm similar to [15], which was used for filtering artifacts out of the radar signal. We modified it not to suppress movement artifacts, but to extract them.

Once a movement event was detected, the extraction of features for analyzed data fragment was performed. In our previous research [11] we showed that the following parameters are useful for fall events classification duration of event

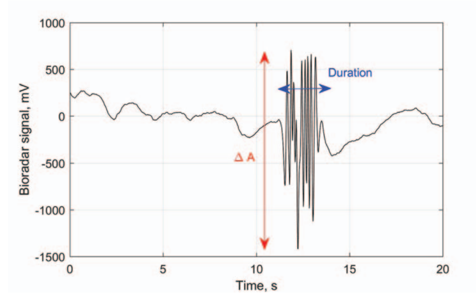

Fig. 3. Sitting on a chair movement pattern.

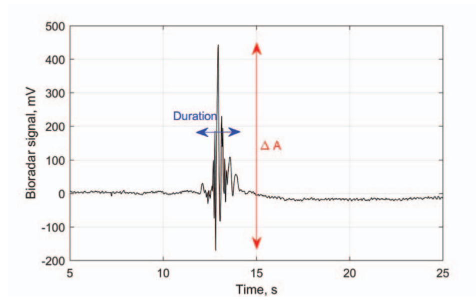

Fig. 4. Fall movement pattern.

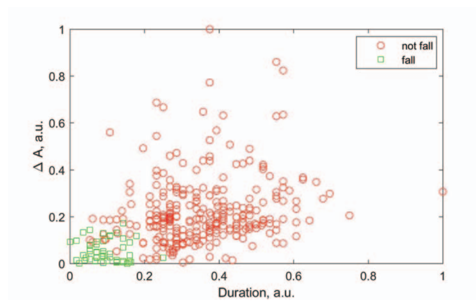

Fig. 5. Scatter plot for duaration and standard deviation of artifacts.

and variation of signal amplitude (A). The estimation of these parameters was done automatically. The Fig. 3 and 4 present patterns of raw bioradar signal with marked classification features for both artifacts for two different movement patterns: sitting down of a chair and falling, respectfully.

After features estimation obtained data were summarized into a table containing classification parameters normalized using min-max normalization technique. A scatter plot for these features is shown in Fig. 5.

To separate “fall” from “not fall” events we tried two types of discriminant analysis: linear (LDA) and quadratic (QDA).

IV. RESULTS

We used well known method named a leave-one-subject-out cross-validation to prevent overtraining of the classifiers. The data for two examinees were used for training the classifiers. The remaining examinee data were used to evaluate the classifiers performance. These steps were repeated three times

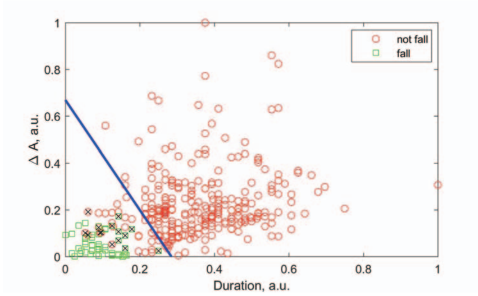

Fig. 6. Results of LDA with error rate 0.04 (border line is in blue).

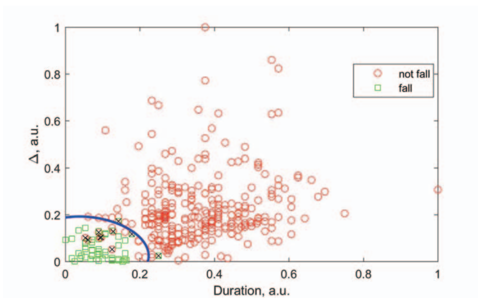

Fig. 7. Results of QDA with error rate 0.04 (border line is in blue).

TABLE III
PERFORMANCE EVALUATION

		LDA		QDA	
		Predicted Class			
		Not fall	Fall	Not fall	Fall
Actual Class	Not fall	280	7	280	7
	Fall	8	43	4	47

	LDA	QDA
Accuracy, %	95.6	97.0
Sensitivity, %	97.5	97.5
Specificity, %	74.5	90.1
AUC, %	98.7	98.8
Cohens kappa, %	82.5	88.8

with changing examinees included into training and testing dataset.

For the evaluation of the classification performance confusion matrix and Cohens kappa coefficient were computed. Moreover, we estimated classification accuracy, sensitivity, specificity and area under receiver operation characteristics curve (AUC) in order to insure comparability with similar studies which were not reported Cohens kappa values.

In Fig. 6 and 7 the results of data classification by LDA and QDA are shown, respectively. The border lines founded by the classifiers are in blue. Wrongly classified samples are marked with black crosses. It can be clearly seen that QDA performed better than LDA.

In Table III the confusion matrices and other classification performance parameters are given for both applied methods of classification.

V. CONCLUSSION

In this work, we presented the results of studies carried out to confirm the possibility of using bioradar for the fall detection. Different types of discriminant analysis were tested to classify movement patterns detected by the bioradar into 'fall' and 'not fall' events. Classifiers were evaluated on the experimental dataset recorded by a continuous wave radar: BioRASCAN-4. The dataset contains 338 records of various basic movements (including 51 fall records) for three examinees. For classification features of bioradar signals in time domain were used. The performance of the classifiers was evaluated calculating classification accuracy and Cohens kappa coefficient.

QDA classifier showed higher accuracy and value of Cohens kappa coefficient than LDA (97.0 vs. 95.6 % and 88.8 vs. 82.5 %, respectively). Thus, utilization of QDA is preferable over the LDA with bioradar movement patterns classification in time domain. It is worth mentioning, that as the scatter plots for "fall" and "not fall" events are overlapping, it is not possible to get perfect classification results by using only two proposed classification features. Therefore, the classification algorithm should be improved by using additional features to be applied in real life.

The future plans are mainly focused on enriching experimental dataset of different motion patterns in the bioradiolocation signals and extension of number of classification parameters, which may help in decreasing the number of false alarms and improve the specificity of the classifiers.

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