Importance of the Bioradar Signal Preprocessing in Fall Detection

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Abstract— This paper describes results of fall detection study with a non-contact bioradiolocation method. The exploration of the impact of the accuracy of determining event length on classification is discussed. In order to investigate this question an analysis including the machine learning classification was performed. We compare performance of two machine learning algorithms: the support vector machines and "K-nearest neighbors" method. The results demonstrated that inaccuracy in determination of length of event has a minor influence on the final classification performance.

1. INTRODUCTION

The world's population is ageing: virtually every country in the world is experiencing growth in the number and proportion of older persons in their population [1]. In Russia, more than 20% of citizens have already celebrated their sixtieth birthday. As known, aging process involves increased susceptibility to age-related diseases and degradation of many systems and organs of the body, which impairs the daily quality of life and gradually increases the risk of fall. Fall incidents are considered to be the most dangerous cause of accidents for elderly people, and represent also the third cause of chronic disability. However, the most of fall consequences can be prevented or eased if the wounded is discovered timely and accurate. Moreover, immediate help after a fall can significantly reduce health care costs among the aging population [2]. Therefore, timely and accurate fall detection is a very important task, especially in case of an elderly who lives alone. So, in recent years, research of an effective fall detection method has become a question that involves more and more scientists worldwide.

There is a variety of wearable devices for motion activity tracking and fall detection based on movement sensors (e.g., accelerometers and gyroscopes) in the market [3, 4]. However, wearable devices are not always comfortable to use, and suffer from a significant false-positive rate. Moreover, the user might forget to put it on regularly, which is quite common type of situations not only for elderly people. In the case of video-cameras technologies, walls and fabrics become optically opaque obstacle, and also such equipment is sensitive to lighting conditions [5, 6]. Privacy issues do not allow to use such systems to watch over a bathroom zone, where the chance to fall is high [7]. There are some recent studies indicating the feasibility of radar-based systems usage in the fall detection [8–10]. The general concept of the majority of these works is the development of a classifier for some characteristics of registered signal in the frequency domain. The reason for this is that falling is considered as a high-energy event in 70–100 Hz frequency range. In this paper, we investigated features of classification extracted from the bioradar signal in time domain, which can simplify the processing algorithm greatly.

In similar studies length of event (fall or not fall) was used as a classification parameters. However, there are a variety of approaches for estimating length of event, and now impact of the accuracy of determining this parameter to classification is unknown. In order to investigate this question was performed an analysis includes the machine learning classification.

2. METHODS AND EXPERIMENTS

We performed our analysis on a dataset of various basic movements that was recorded by continuous-wave radar: BioRASCAN-4 designed at Bauman Moscow State Technical University (BMSTU) [11]. It operates at 8 probing frequencies (each of them has two quadratures) in the range 3.6—4.0 GHz. The maximum power density radiated by the bioradar is equal to $1.36\,\mu\mathrm{W/cm^2}$. Such a value satisfies the Russia safety standard for microwave emission, which is $25\,\mu\mathrm{W/cm^2}$ in the frequency range of 3–300 GHz (for 24 hours exposure) [12]. The technical characteristics of the BioRASCAN-4 are presented in Table 1. The radar data sets were collected at the Remote Sensing Laboratory (BMSTU).

The bioradar signals were recorded for different types of everyday movements, including turning 90 and 180 degrees, arm motion up and down, going in and out of the room, sitting on the chair and standing up from it. Examinees were mimicking falls on a previously prepared floor covering (feather pillows) to make the falling as save as possible. The scheme of the experiment is given in Fig. 1. Three healthy volunteers participated in stage of the experiments. Each of them gave the informed consent prior to the participation. The elderly also took part in the accumulation of the dataset (except for fall movements). The accumulated database contains records of 244 different movements including 65 with fall pattern (for each frequency).

Table 1. Technical characteristics of BioRASCAN-4.

Number of frequencies	8
Frequency range	3.6 to 4.0 GHz
Dynamic range of the recording signals	60 dB
Gain constant	20 dB
RF output	< 3 mW
Sensitivity	1 mm

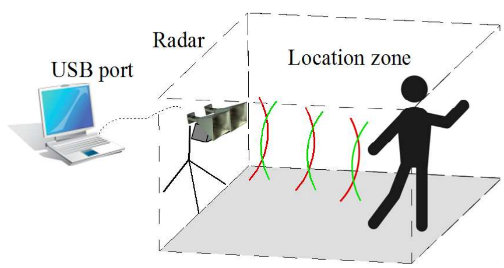

Figure 1. The scheme of experiment.

3. DATA PROCESSING

The preprocessing algorithm involves several sub-stages shown in Fig. 2, similar to the previous study [9]. A received radar signal, which consists of a two quadratures for each probing frequency, is data-in of algorithm. Duration of the records may vary. Each bioradar record consists of 16 signals (8 operating frequencies, each of them has I and Q quadrature), which were recorded simultaneously. The first stage starts from automatic selection one of the quadratures (choosing the one with higher energy level). Further, a chosen record is divided into intervals of 10 s duration. Each interval was analyzed by threshold function similar to [13] that determines exactly where important events occurred in the data sequence. Once an event is detected, the extraction of features for analyzed data fragment is performed. Data from our previous research [9] have shown that the following parameters are useful for fall events classification — *length of event* t and *variation of signal amplitude* ΔA. At the completion of feature extraction phase obtained data go to the summary table.

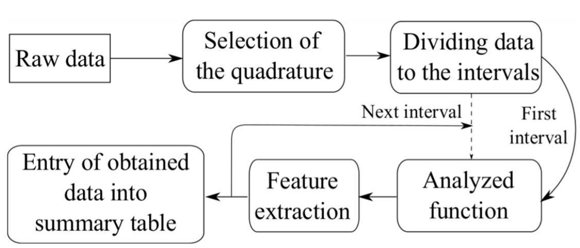

Figure 2. Scheme of the preprocessing algorithm.

Therefore, upon processing of all records by the above algorithm, the obtained summary table with data of classification parameters was used to further stage of features investigating by using machine-learning algorithms. Data preprocessing and further modeling were done utilizing MATLAB 2015a.

In order to estimate the impact of the accuracy of determining length of event — t, a uniform noise was generated and added to obtained data of t parameter. The noise was generated with mean equal to 0 and the following values of maximum and minimum: $+/-0.1$ s, $+/-0.5$ s, $+/-1$ s. That numbers was chosen by reasons of minimum value of t is equal 1 second.

After that step the datasets with noise was normalized. Scatter plot for one of the result datasets is shown in Fig. 3.

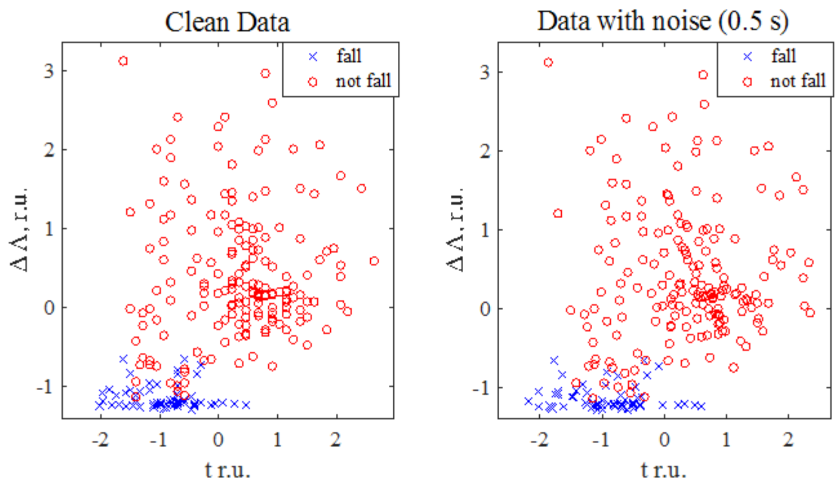

Figure 3. Scatter plot of obtained values of classification parameters (probing frequency = 3, 8 GHz).

In order to get a comprehensive assessment of the investigated question was compared two most exploited machine learning algorithms: Support Vector Machines (SVM) [14] and K-Nearest Neighbors (KNN) [15].

As known, SVM method in initial version is a binary classifier, which based on finding the best hyperplane in the feature space that gives the largest minimum distance to the training examples according to the class value. KNN is a classifier, which is based on calculation distance (Euclidean or another) from a new instance to each instance in the training dataset. After that it assigns the new instance to the majority class label from the closest k neighboring instances in the training dataset.

Table 2. Performance evaluation for dataset without noise.

Level of noise = 0	**Coarse Gaussian SVM**		**Linear SVM**		**Cubic KNN**		**Weighted KNN**	
	Actual Class		***Actual Class***		***Actual Class***		***Actual Class***	
Predicted Class	***Not fall***	***Fall***	***Not fall***	***Fall***	***Not fall***	***Fall***	***Not fall***	***Fall***
Not fall	167	1	170	8	168	2	166	1
Fall	12	64	9	57	11	63	13	64
FPR	6.7%		5.3%		6.1%		7.26%	
FNR	1.5%		12.31%		3.1%		1.5%	

Table 3. Cohen's kappa evaluation for all classification results (datasets with different level of noise).

Level of noise	**Coarse Gaussian SVM**	**Linear SVM**	**Cubic KNN**	**Weighted KNN**	**Mean**
	0.8906	0.8500	0.8895	0.8827	0.8782
$+/-$ **0.1 c**	0.8827	0.8771	0.8895	0.8827	0.8830
$+/-$ **0.5 c**	0.8827	0.8514	0.8555	0.8906	0.8701
$+/-$ **1 c**	0.8827	0.8608	0.8805	0.8917	0.8789

The four classifiers were implemented: Linear SVM, Coarse Gaussian SVM, Cubic KNN and Weighted KNN. All of the classifiers were used with their default parameters as implemented in the MATLAB Classification Learner toolbox.

For the evaluation of the implemented classifiers and preventing overfitting, the cross validation k-folds technique was used with $k = 5$. For the evaluation of the classification performance confusion matrix and Cohen's kappa coefficient were computed (Table 3). In Table 2 the confusion matrices and other classification performance parameters are given for both applied methods of classification. The level of obtained accuracy was assessed as false positive rate (FPR) and false negative rate (FNR). The results of different classifiers generally show a good classification performance. However, the Coarse Gaussian SVM classifier demonstrated the best result.

4. CONCLUSION

In this study, we aimed to determine whether the accuracy of estimation length of event parameter is important for development of fall detection classifier with good performance. Moreover, we tried to estimate the advantages classification based only on time domain parameters. From the present study, the following conclusion can be drawn:

- The inaccuracy in determination of length of event has a minor influence on the final classification performance.
- The level of errors for developed classifiers is commensurable with results of other works on this theme [3, 6, 8, 10].

These results (FNP $> 5\%$) can be explained by small number of classification parameters. However, in general the developed classifier has shown a sufficient level of accuracy ($> 94\%$). Moreover, the size of the experimental dataset we used is much bigger than datasets in similar works [8, 10].

The future research developments will be performed in the following main directions: enriching dataset of different motion patterns in the bioradiolocation signals and extension of number of classification parameters, which should allow diminishing the number of false alerts.

REFERENCES

1. United Nations, Department of Economic and Social Affairs, Population Division, World Population Prospects, The 2013 Revision, CD-ROM Edition, 2013.
2. Todd, C. and D. Skelton, "What are the main risk factors for falls among older people and what are the most effective interventions to prevent these falls?" Copenhagen, WHO Regional Office for Europe, 2004 (Health Evidence Network report; http://www.euro.who.int/document/E82552.pdf, accessed Oct. 15, 2016).
3. Gjoreski, M., H. Gjoreski, and M. Lustrek, "How accurately can your wrist device recognize daily activities and detect falls?" *Sensors*, Vol. 16, 800, 2016.
4. Chuah, Y. and J. Lee, "Fall detection of elderly people in bathroom: A complement method of wearable device," *International Journal of Applied Engineering Research*, ISSN 0973-4562, Vol. 11, No. 6, 4184–4186, 2016.
5. Kumar, D. P., Y. Yun, and I. Y. H. Gu, "Fall detection in RGB-D videos by combining shape and motion features," *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 1337–1341, Shanghai, 2016.
6. Mundher, Z. A., "A real-time fall detection system in elderly care using mobile robot and kinect sensor," *International Journal of Materials, Mechanics and Manufacturing*, Vol. 2, No. 2, May 2014.
7. De Vito, C. A., D. A. Lambert, R. W. Sattin, S. Bacchelli, A. Ros, and J. G. Rodriguez, "Fall injuries among the elderly. Community-based surveillance," *J. Am Geriatr Soc.*, Vol. 36, No. 11, 1029–1035, Nov. 1988.
8. Wu, Q., Y. D. Zhang, W. Tao, and M. G. Amin, "Radar-based fall detection based on Doppler time-frequency signatures for assisted living," *IET Radar, Sonar & Navigation, Special Issue on Application of Radar to Remote Patient Monitoring and Eldercare*, Vol. 9, No. 2, 164–172, Feb. 2015.
9. Dremina, M. K. and L. N. Anishchenko, "Contactless fall detection by means of CW bioradar," *PIERS Proceedings*, Shanghai, China, Aug. 8–12, 2016.

10. Liang, S. L., M. Popescu, M. Skubic, M. Rantz, T. Yardibi, and P. Cuddihy, "Automatic fall detection based on doppler radar motion signature," *Proceedings of the 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, 222–225, 2011.
11. Remote Sensing Laboratory, http://www.rslab.ru/english/.
12. SanPin 2.2.4/2.1.8.055-96, "Radiofrequency electromagnetic radiation under occupational and living conditions".
13. Anishchenko, L., G. Gennarelli, A. Tataraidze, E. Gaysina, F. Soldovieri, and S. Ivashov, "Evaluation of rodents' respiratory activity using a bioradar," *IET Radar, Sonar & Navigation*, 7, 2015.
14. Cristianini, N. and J. Shawe-Taylor, *An Introduction to Support Vector Machines and Other Kernel-based Learning Methods*, Cambridge University Press, Cambridge, UK, 2000.
15. Aha, D. W., D. Kibler, and M. K. Albert, "Instance-based learning algorithms," *Mach. Learn.*, Vol. 6, No. 1, 37–66, 1991.