21st IMEKO TC4 International Symposium and
19th International Workshop on ADC Modelling and Testing
Understanding the World through Electrical and Electronic Measurement
Budapest, Hungary, September 7–9, 2016

Impulse-radar sensors *versus* depth sensors when applied for monitoring of elderly and disabled persons

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***Abstract* – This paper is devoted to two sensor technologies that may be employed in care services for elderly and disabled persons. The performance of monitoring systems, based on impulse-radar sensors and on depth sensors, has been systematically compared in a series of experiments which involved the estimation of several healthcare-informative quantities on the basis of data from such sensors. The results of the experiments have shown that, although the estimates based on the radar data are less accurate than those based on the depth data, both types of sensors provide information useful for the medical and healthcare users of the monitoring systems.**

***Keywords* – impulse-radar sensor, depth sensor, healthcare monitoring, measurement data processing**

I. INTRODUCTION

The life expectancy has been growing in Europe for many years, while the healthy life expectancy has been slightly diminishing since the last decade of the XXth century [1]. Hence the growing importance of research on new technologies that could be employed in monitoring systems supporting care services for elderly and disabled persons. The capability of those systems to detect dangerous events, such as person's fall, is of key importance [2]. However, those systems are expected not only to detect dangerous events, but also to predict those events on the basis of acquired data, and therefore contribute to the prevention of such events. The analysis of gait, as well as of the itinerary and timing of activities of the monitored persons, may thus contribute to prevention [3, 4].

This paper is focused on the systems for non-intrusive monitoring of the movements of elderly and disabled persons in their home environment, based on impulse-radar sensors and depth sensors. Several quantities, carrying information important for medical and healthcare services, which can be estimated on the basis of data from such sensors, are described. The results of experiments, aimed at comparing the measurement uncertainty, achievable in case of these two types of sensors, are presented.

II. LITERATURE OVERVIEW

There are three main categories of monitoring techniques already applied in healthcare practice – vision-based [4–6], environmental [7–9] and wearable [10–12]. There are also two emerging categories: radar-based [13–15] and depth-sensor-based techniques [16–18]; the attempts to apply them for monitoring of elderly and disabled persons are mainly motivated by the conviction that they may be less intrusive than vision-based solutions, less cumbersome than the wearable solutions, and less invasive with respect to the home environment than the environmental solutions. The references [4–18] are provided here as representative examples of the abundant literature concerning monitoring techniques, published in 2014–2016 only.

The most attractive feature of the radar-based monitoring techniques is the possibility of the through-the-wall monitoring of human activity, thus allowing for monitoring in the whole area of the household without the need to install sensors in each room. The research options related to this topic may be broadly classified according to the spectrum of the radar signals applied. Some researchers prefer to focus on narrow-band solutions, especially those using the Doppler principle [15, 19], whereas others opt for ultrawideband solutions, especially those based on pulse-type signals [20, 21],

whose high time resolution facilitates very precise position estimation which – in turn – makes possible a variety of commodity applications. Radar-based systems have been proposed for applications varying from walking velocity estimation to fall detection [19, 21, 22].

Since several years numerous attempts have been made to apply the depth sensors for monitoring of elderly and disabled persons. The applicability potential behind this monitoring technique is related to the low price of depth sensors which are installed in such common gadgets as the Microsoft Kinect devices. Two last years brought numerous publications where the Kinect depth-imaging cameras are used for patients monitoring; representative examples are provided in [17, 23–25]. Recently, the new generation of Kinect devices – the so-called Kinect V2 – has gained interest among researchers; the 2015 paper by Lachat *et al.* [26] is providing a sound overview of the capabilities of the new sensor.

The possibility of merging depth sensors and wearable accelerometers has also been recently studied [27, 28]; Caroppo *et al.* have proposed the fusion of depth sensors, accelerometers and radar sensors [29].

The relevance of features related to gait analysis in monitoring of elderly persons, and in particular – in fall prevention, has been emphasised in several recent papers [4, 30–32]. The 2016 book chapter by Baldewijns *et al.* [3] contains a comprehensive overview of fall prevention and detection methods, as well as of techniques that can be applied for this purpose. The *Just Checking* system [33] is a commercial example of a system for monitoring of elderly persons, based on movement sensors and door motion sensors, without vision-based, wearable and environmental components.

III. COMPARED METHODS OF DATA PROCESSING

A set of procedures for estimation of the following quantities, useful in monitoring elderly and disabled persons, has been implemented:

- average walking velocity,
- distance travelled in a selected period of time,
- frequency of sudden turns (which may result from the monitored person's confusion),
- time spent in selected areas of the household at different hours of a day (which allows for observing long-term trends and anomalies in the person's behaviour),
- time spent in motion (which may indicate the monitored person's level of activity, or – at night – bad sleep).

All the above-mentioned quantities can be estimated using data representative of the two-dimensional coordinates of the monitored person's position.

A. Estimation of position

The coordinates of the monitored person's position can be estimated on the basis of radar data according to the following scheme [34]:

- extraction of the useful signal from the raw data,
- estimation of the distances between the monitored person and the sensors,
- estimation of the two-dimensional coordinates of the monitored person's position.

The same coordinates can be estimated on the basis of depth images acquired by means of the depth sensors according to the following scheme [35]:

- extraction of the monitored person's silhouette,
- estimation of the silhouette centre coordinates,
- transformation of the image coordinate system into the spatial coordinate system.

The principles of estimation of the two-dimensional position by means of the impulse-radar sensors and the depth sensors are illustrated in Fig. 1 and Fig. 2.

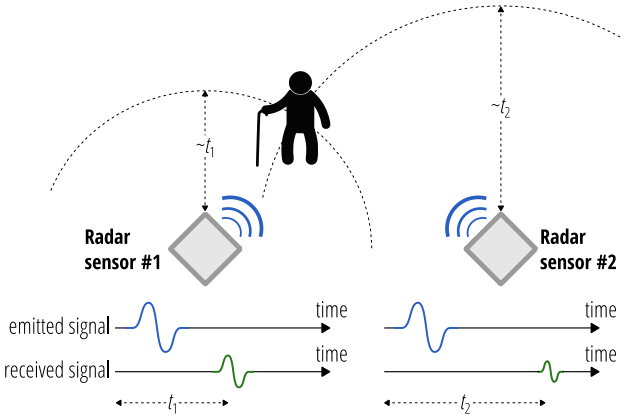

Fig. 1. Estimation of two-dimensional position by means of two impulse-radar sensors.

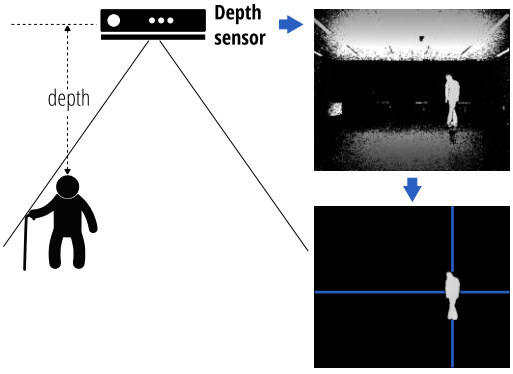

Fig. 2. Estimation of two-dimensional position by means of a depth sensor.

B. Detection of motion

Motion can be detected by comparing the distance, travelled in a fixed period of time T_m, with a threshold ϑ. The values of the parameters T_m and ϑ should be empirically optimised to prevent small deviations in the position estimates – caused, for example, by the movement of the monitored person's limbs – from being considered as motion. The values $T_m = 0.45\,\mathrm{s}$ and $\vartheta = 0.15\,\mathrm{m}$ have been selected via numerical optimisation.

For smoothing the sequences generated by the algorithm of motion detection, one-dimensional morphological opening and closing filters have been used [36].

C. Estimation of walking velocity

Two methods for the estimation of the average walking velocity have been implemented. The first method involves numerical differentiation of the monitored person's trajectory and averaging the velocity estimates over the time intervals in which motion has been automatically detected. A regularised version of the central-difference method, involving the optimisation of the differentiation step, has been used for differentiation. To avoid underestimation of the average velocity, the periods during which the monitored person is accelerating or decelerating have been rejected. This has been done by applying one-dimensional morphological erosion to the Boolean sequence representative of the results of motion detection.

The second method involves estimation of the so-called transfer time, *i.e.* time needed for the monitored person to pass through a predefined area [3]. In practical applications, an area such as a corridor – through which the monitored person passes frequently without stopping – should be chosen for this goal. The average walking velocity is estimated on the basis of the detected moments at which the monitored person enters and leaves the area, and the distance between the points at which it happens.

D. Detection of sudden turns

The movement direction can be estimated by computing the four-quadrant inverse tangent of two position estimates, obtained at two different time points. Small insignificant movements can cause noise in the direction estimates; it may be filtered out by comparing the distance travelled in the interval between the two time points with a threshold and eventually keeping the previous direction estimate instead of the updated one.

The monitored person's sudden turns can be detected by comparing the average walking direction in two neighbouring time windows and returning a positive decision whenever the difference exceeds a threshold. The threshold values from the range of [100°, 145°] have allowed for faultless detection of sudden turns in the experiments reported in this paper.

The movement direction is represented by a number from the range $(-\pi, \pi]$. Due to the periodicity of this representation, a small change in the direction can cause a large difference in that number when it is close to π or $-\pi$, thus causing false turn detections. Such jumps have to be smoothed out by extending the domain to $(-\infty, \infty]$ and correcting the direction estimate every time the difference between two consecutive estimates exceeds the value of π.

E. Estimation of travelled distance

Prior to estimation of the travelled distance, outlying position estimates have to be removed by means of a median filter. Then, the travelled distance can be estimated by summing up the distances between consecutive position estimates.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In a series of experiments, the performance of a monitoring system based on impulse-radar sensors and the one based on a depth sensor has been compared. The data for those experiments have been acquired by means of both types of sensors simultaneously. The uncertainty of the estimates of the healthcare-informative quantites, obtained on the basis of those data, has been evaluated.

In order to enable the monitored person to walk along predefined trajectories, marks have been placed on the floor at 21 points (called *reference points* hereinafter) located at the nodes of a regular grid, as shown in Fig. 3. Walking with the velocity of assumed value (called *reference value* hereinafter) has been ensured by making half-meter steps in equal time intervals, signalled by a metronome set to an appropriate tempo.

The statistics of the errors in the estimates of the healthcare-informative quantites are presented in Table 1.

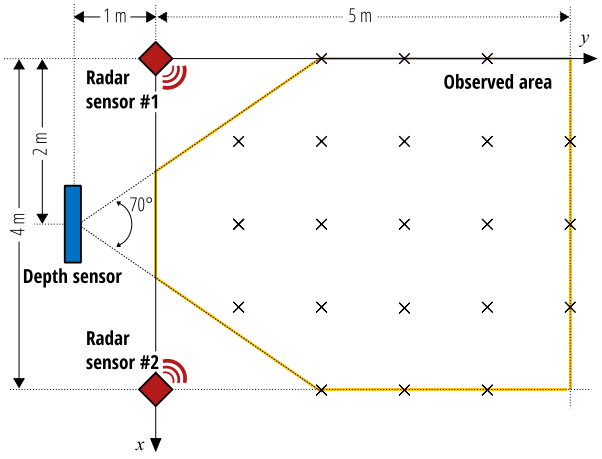

Fig. 3. The experimental setup; the crosses indicate the reference points, i.e. the points where marks have been placed on the floor.

Exemplary trajectories of the monitored person, estimated in of the experiments, are shown in Fig. 4. The mean absolute errors of the position estimates at different reference points are shown in Fig. 5.

It follows from Table 1 that the system based on the depth sensor outperforms the one based on the impulse-radar sensors in terms of three indicators of uncertainty (mean error, standard deviation of errors and maximum error) almost for all estimated quantities. It is a consequence of the lower uncertainty of the position estimates obtained by means of the depth-sensor-based system when compared with the radar-based one. However, it should be noted that also the estimates provided by the

Table 1. Uncertainty indicators for the estimates of healthcare-informative quantites.

	Impulse-radar sensors	**Depth sensor**
position		
mean error	–0.08 m	–0.03 m
standard deviation of errors	0.27 m	0.06 m
maximum error	1.38 m	0.19 m
motion start/stop time		
mean error	0.36 s	–0.10 s
standard deviation of errors	0.59 s	0.26 s
maximum error	1.83 s	0.87 s
walking velocity (differentiation-based method)		
mean error	–0.04 m/s	–0.02 m/s
standard deviation of errors	0.10 m/s	0.03 m/s
maximum error	0.29 m/s	0.09 m/s
walking velocity (transfer-time-based method)		
mean error	0.02 m/s	0.01 m/s
standard deviation of errors	0.13 m/s	0.02 m/s
maximum error	0.41 m/s	0.05 m/s
walking direction		
mean error	5.6°	–0.4°
standard deviation of errors	21.6°	6.6°
maximum error	100.9°	20.6°
sudden turn		
undetected turns	0	0
falsely detected turns	0	0
travelled distance		
mean relative error	7.7%	8.1%
standard deviation of relative errors	11.8%	3.2%
maximum relative error	26.3%	16.0%

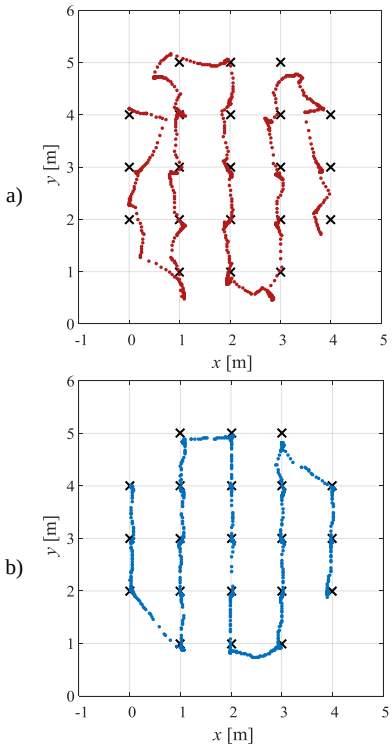

Fig. 4. Exemplary trajectories of the monitored person, estimated on the basis of the radar data (a) and the depth data (b).

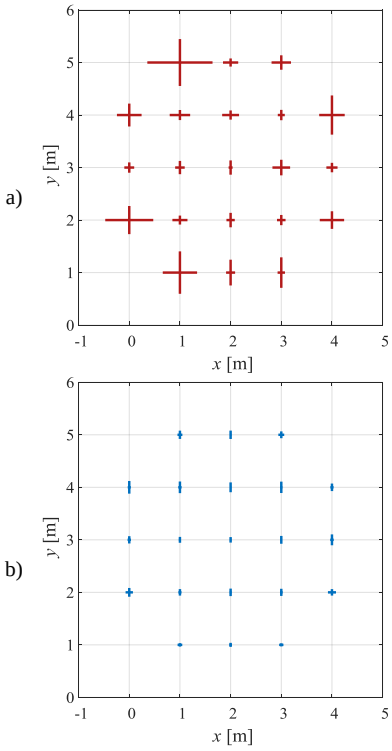

Fig. 5. Errors in the position estimates obtained on the basis of the radar data (a) and the depth data (b); the length of the arms of each cross is proportional to the mean absolute error of the estimated x and y coordinates at different reference points.

radar-based system are quite useful for the medical and healthcare staff in detecting long-term trends and anomalies in the behaviour of a monitored person.

It can be seen in Fig. 5a that the position estimates, obtained on the basis of radar data, are corrupted with larger errors for the points close to the borders of the monitored area than for the points located in its centre. Therefore, the area should be selected in such a way as to ensure that the monitored person is passing frequently through its centre. However, the radar sensors can be used for estimation of the time spent by the monitored person in selected areas away from the centre, such as the kitchen or bedroom, since the uncertainty is there sufficiently low to correctly identify the room.

The results of the presented comparison seem to speak in favour of the monitoring system based on the depth sensor. However, it has also some disadvantages if compared to the radar-based system:

- First, the coverage of a depth sensor is limited to a single room; even if multiple depth sensors are used for monitoring of several rooms in a household, they are still unable to track a person in certain hidden places, *e.g.* behind furniture; on the other hand, the radar sensors' ability of through-the-wall monitoring allows for covering a larger area without the need of installing multiple sensors.
- Second, the amount of data, acquired by means of the depth sensor, is very large, and the computational cost of data processing is greater than in case of the radar-based system.
- Third, even though the acquisition of depth data does not violate the privacy of the monitored persons, it may be less acceptable for them than the acquisition of radar data – which do not provide silhouette information.
- Fourth, it has been observed in the completed experiments that the fraction of missing data may be very high in case of the depth sensor exposed to strong sunlight – which does not affect the radar sensors at all.

Both types of sensors studied in this paper can be used to support medical and healthcare staff in monitoring elderly and disabled persons, each having its advantages and disadvantages. Sensor fusion is also possible, *e.g.* if the radar-based position estimates are used for enabling the acquisition of data by depth sensors only when the monitored person is within their coverage.

V. CONCLUSION

The novelty of the study, whose results are presented in this paper, consists in systematic comparison of two relatively new techniques for monitoring of elderly and disabled persons, *viz.* impulse-radar sensors and depth sensors. This comparison is based on 21 application-specific criteria, *viz.* three indicators of uncertainty defined on the estimates of the following seven healthcare-specific quantities: position, motion start/stop time, walking velocity (determined by means of the differentiation-based method), walking velocity (determined by means of the transfer-time-based method), walking direction, sudden turn, and travelled distance. The study has shown that both tested sensor technologies can be used for supporting medical and healthcare staff in monitoring elderly and disabled people, and has revealed their strong and weak points. The analysis of those characteristics suggests that the combination of both types of sensors, followed by adequate data fusion, could be advantageous.

ACKNOWLEDGMENT

This work has been accomplished within the project PL12-0001 financially supported by *EEA Grants – Norway Grants* (*http://eeagrants.org/project-portal /project/PL12-0001*).

REFERENCES

[1] "Healthy Life Years", available: http://www.healthy-life-years.eu/ (as of 2016-06-22).

[2] J. Hamm, A. G. Money, A. Atwal, and I. Paraskevopoulos, "Fall prevention intervention technologies: A conceptual framework and survey of the state of the art", *Journal of Biomedical Informatics*, vol. 59, pp. 319–345, 2016.

[3] G. Baldewijns, G. Debard, B. van Den Broeck, M. Mertens, P. Karsmakers, T. Croonenborghs, and B. Vanrumste, "Fall prevention and detection", *Active and Assisted Living: Technologies and Applications*, F. Florez-Revuelta and A. A. Chaaraoui, eds., pp. 1–22, Herts, UK: IET, 2016.

[4] G. Baldewijns, S. Luca, B. Vanrumste, and T. Croonenborghs, "Developing a system that can automatically detect health changes using transfer times of older adults", *BMC medical research methodology*, vol. 16, no. 1, pp. 1–17, 2016.

[5] Jia-Luen Chua, Yoong Choon Chang, and Wee Keong Lim, "A simple vision-based fall detection technique for indoor video surveillance", *Signal, Image and Video Processing*, vol. 9, no. 3, pp. 623–633, 2015.

[6] Weiguo Feng, Rui Liu, and M. Zhu, "Fall detection for elderly person care in a vision-based home surveillance environment using a monocular camera", *Signal, Image and Video Processing*, vol. 8, no. 6, pp. 1129–1138, 2014.

[7] R. Castaldo, and L. Pecchia, "Preliminary Results from a Proof of Concept Study for Fall Detection via ECG Morphology", *Proc. XIV Mediterranean Conference on Medical and Biological Engineering and Computing*, pp. 205–208, 2016.

[8] M. S. Khan, Miao Yu, Pengming Feng, Liang Wang, and J. Chambers, "An unsupervised acoustic fall detection system using source separation for sound interference suppression", *Signal Processing*, vol. 110, pp. 199–210, 2015.

[9] D. Zhang, H. Wang, Y. Wang, and J. Ma, "Anti-Fall: A Non-intrusive and Real-time Fall Detector Leveraging CSI from Commodity WiFi Devices",

Lecture Notes in Computer Science, vol. 9102, pp. 181–193, 2015.

[10] M. A. Brodie, S. R. Lord, M. J. Coppens, J. Annegarn, and K. Delbaere, “Eight-Week Remote Monitoring Using a Freely Worn Device Reveals Unstable Gait Patterns in Older Fallers”, *IEEE Transactions on Biomedical Engineering,* vol. 62, no. 11, pp. 2588–2594, 2015.

[11] B. Wójtowicz, A. Dobrowolski, and K. Tomczykiewicz, “Fall Detector Using Discrete Wavelet Decomposition And SVM Classifier”, *Metrology and Measurement Systems,* vol. 22, no. 2, pp. 303–314, 2015.

[12] Yung-Gi Wu, and Sheng-Lun Tsai, “Fall detection system design by smart phone”, *International Journal of Digital Information and Wireless Communications,* vol. 4, no. 4, pp. 474–478, 2014.

[13] O. Boric-Lubecke, V. M. Lubecke, A. D. Droitcour, Byung-Kwon Park, and A. Singh, Eds., *Doppler Radar Physiological Sensing*. Hoboken, NJ, USA: John Wiley & Sons, Inc. 2016.

[14] J. Sachs, and R. Herrmann, “M-sequence-based ultra-wideband sensor network for vitality monitoring of elders at home”, *IET Radar, Sonar & Navigation,* vol. 9, no. 2, pp. 125–137, 2015.

[15] B. Y. Su, K. C. Ho, M. Rantz, and M. Skubic, “Doppler Radar Fall Activity Detection Using The Wavelet Transform”, *IEEE Transactions on Biomedical Engineering,* vol. 62, pp. 865–875, 2015.

[16] M. Tanaka, "Application of depth sensor for breathing rate counting", *Proc. Asian Control Conference*, pp. 1–5, 2015.

[17] D. Webster, and O. Celik, “Systematic review of Kinect applications in elderly care and stroke rehabilitation”, *Journal of Neuroengineering and Rehabilitation,* vol. 11, no. 108, pp. 1–24, 2014.

[18] Young-Ho Suh, Sang Keun Rhee, and Kang-Woo Lee, "Continuous location tracking of people by multiple depth cameras", *Proc. International Conference on Information and Communication Technology Convergence*, pp. 170–172, 2015.

[19] M. G. Amin, Y. D. Zhang, F. Ahmad, and K. C. D. Ho, “Radar Signal Processing for Elderly Fall Detection”, *IEEE Signal Processing Magazine,* vol. March, pp. 71–80, 2016.

[20] S. Gezici, and H. V. Poor, “Position Estimation via Ultra-Wide-Band Signals”, *Proceedings of the IEEE,* vol. 97, no. 2, pp. 386–403, 2009.

[21] X. Dai, Z. Zhou, J. J. Zhang, and B. Davidson, “Ultra-wideband radar-based accurate motion measuring: human body landmark detection and tracking with biomechanical constraints”, *IET Radar, Sonar & Navigation,* vol. 9, no. 2, pp. 154–163, 2015.

[22] C. Garripoli, M. Mercuri, P. Karsmakers, Ping Jack Soh, G. Crupi, G. A. E. Vandenbosch, C. Pace, P. Leroux, and D. Schreurs, “Embedded DSP-Based Telehealth Radar System for Remote In-Door Fall Detection”, *IEEE Journal of Biomedical and Health Informatics,* vol. 19, no. 1, pp. 92–101, 2015.

[23] Chen Chen, R. Jafari, and N. Kehtarnavaz, “Improving Human Action Recognition Using Fusion of Depth Camera and Inertial Sensors”, *IEEE Transactions on Human-Machine Systems,* vol. 45, no. 1, pp. 51–61, 2015.

[24] E. E. Stone, and M. Skubic, “Fall detection in homes of older adults using the Microsoft Kinect”, *Biomedical and Health Informatics, IEEE Journal of,* vol. 19, no. 1, pp. 290–301, 2015.

[25] A. Yajai, A. Rodtook, K. Chinnasarn, and S. Rasmequan, “Fall detection using directional bounding box”, *Proc. 2015 International Joint Conference on Computer Science and Software Engineering*, pp. 52–57, 2015.

[26] E. Lachat, H. Macher, M. Mittet, T. Landes, and P. Grussenmeyer, “First experiences with kinect v2 sensor for close range 3d modelling”, *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences,* vol. 40, no. 5, pp. 93–100, 2015.

[27] Chen Chen, R. Jafari, and N. Kehtarnavaz, “A survey of depth and inertial sensor fusion for human action recognition”, *Multimedia Tools and Applications*, no. December, pp. 1–21, 2015.

[28] M. Kepski, and B. Kwolek, “Embedded system for fall detection using body-worn accelerometer and depth sensor”, *Proc. 2015 IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications*, pp. 755–759, 2015.

[29] A. Caroppo, G. Diraco, G. Rescio, A. Leone, and P. Siciliano, "Heterogeneous sensor platform for circadian rhythm analysis", *Proc. Advances in Sensors and Interfaces (IWASI), 2015 6th IEEE International Workshop on*, pp. 187–192, 2015.

[30] M. Lusardi, “Is Walking Speed a Vital Sign?”, *Topics in Geriatric Rehabilitation,* vol. 28, no. 2, pp. 67–76, 2012.

[31] E. Stone, M. Skubic, M. Rantz, C. Abbott, and S. Miller, “Average in-home gait speed: Investigation of a new metric for mobility and fall risk assessment of elders”, *Gait & posture,* vol. 41, no. 1, pp. 57–62, 2015.

[32] P. Thingstad, T. Egerton, E. F. Ihlen, K. Taraldsen, R. Moe-Nilssen, and J. L. Helbostad, “Identification of gait domains and key gait variables following hip fracture”, *BMC geriatrics,* vol. 15, no. 1, pp. 1–7, 2015.

[33] "Just Checking – How the system works", available: http://www.justchecking.co.uk/professionals/how-the-system-works/ (as of 2016-06-29).

[34] J. Wagner, A. Miękina, P. Mazurek, R. Z. Morawski, W. Winiecki, F. F. Jacobsen, K. Øvsthus, T. T. Sudmann, and I. T. Børsheim, “Signal Processing in Two-Module Radar System for Monitoring of Elderly and Disabled Persons”, submitted to: *20th IEEE Signal Processing: Algorithms, Architectures, Arrangements, and Applications Conference*, 21–23 September, 2016, 6 pages.

[35] P. Mazurek, J. Wagner, and R. Z. Morawski, "Acquisition and Preprocessing of Data from Infrared Depth Sensors to be Applied for Patients Monitoring", *Proc. IEEE Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications*, 6 pages, 2015.

[36] L. Koskinen, J. T. Astola, and Y. A. Neuvo, "Soft morphological filters", *Proc. SPIE 1568, Image Algebra and Morphological Image Processing II, 262*, pp. 262–270, 1991.