Healthcare-Oriented Characterisation of Human Movements by Means of Impulse-Radar Sensors and by Means of Accelerometric Sensors

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Abstract: This paper is devoted to the healthcare-oriented characterisation of the human movements by means of the accelerometric and impulse-radar sensors – the sensors that may be employed in care services for monitoring of elderly and disabled persons. Characterisation of the movements in terms of the so-called self-selected walking velocity can be used by the medical and healthcare personnel to assess the overall health status of a monitored person. The quality of the characterisation, based on the measurement data from accelerometric and impulse-radar sensors, has been assessed in a series of real-world experiments which involved the estimation of the instantaneous and mean walking velocity of a person moving according to predefined patterns. Some indicators of uncertainty of the velocity estimation, determined with respect to assumed predefined velocity values, have been used for comparison of the performance of both types of sensors. The experiments have shown that impulse-radar sensors enable one to estimate the mean walking velocity more accurately than the accelerometric sensors: the estimates obtained on the basis of data from the latter sensors are affected by larger bias and are more widely spread around their mean values.

1 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 (*cf. http://www.healthy-life-years.eu/*). 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 (Hamm et al., 2016). However, those systems are expected not only to detect dangerous events, but also to predict those events on the basis of acquired data. The analysis of gait, as well as of the itinerary and timing of activities of the monitored persons, may thus contribute to the prevention (Baldewijns et al., 2016a). 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 (Buracchio et al., 2010, Studenski et al., 2011, Lusardi, 2012, Egerton et al., 2014, Stone et al., 2015, Thingstad et al., 2015, Baldewijns et al., 2016b).

So far, the most popular monitoring technique, already applied in healthcare practice, is based on wearable devices (Bulling et al., 2014, Cola et al., 2014, Luque et al., 2014, Brodie et al., 2015). Those devices do not require a pre-built infrastructure and thus may be used outdoor. The signals from movement sensors (mainly accelerometers and gyroscopes), worn by a monitored person, are transmitted via radio links to a computer and analysed. This solution makes also possible the acquisition of physiological data (such as values of blood pressure, ECG data or EEG data).

Recently, numerous attempts have been made to apply various radar techniques for monitoring of elderly and disabled persons (Cuddihy et al., 2012, Liu et al., 2012, Tomii and Ohtsuki, 2012, Jian et al., 2014, Su et al., 2015, Miękina et al., 2016b). Those attempts are mainly motivated by the conviction that

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those techniques may be less intrusive than vision-based solutions (*e.g.* digital cameras), less cumbersome than wearable solutions (*e.g.* accelerometers and gyroscopes), and less invasive with respect to the home environment than environmental solutions (*e.g.* pressure sensors).

This paper is devoted to the assessment of the uncertainty of the estimation of the walking velocity, on the basis of data acquired by means of impulse-radar sensors and by means of accelerometric sensors. As suggested in the literature, *e.g.* (Fritz and Lusardi, 2009), the walking velocity is highly informative for healthcare experts; for example:

- the velocity lower than 0.6 m/s enables them to predict an increase in the risk of falls and hospitalisation of a monitored person;
- an improvement in walking velocity of at least 0.1 m/s is a useful predictor for well-being;
- a decrease of the same amount is correlated with deterioration of the health status or advancement of disability.

The comparative study, reported in this paper, is based on an extensive set of real-world experiments which comprise:

- simultaneous recording of measurement data from both types of sensors, representative of the gait characteristics of a person moving according to predefined patterns;
- statistical analysis of those data, aimed at determination of certain indicators of uncertainty of the velocity estimation.

Due to the operation principle of both types of sensors, one may expect that the position of a monitored person can be better estimated on the basis of the data from impulse-radar sensors (hereinafter called *radar data* for brevity), and its acceleration – on the basis of data from the accelerometric sensors (hereinafter called *accelerometric data* for brevity). Therefore, despite the fact that both the position and the acceleration may also be of interest for the healthcare personnel, this study is confined to the uncertainty of the estimation of the velocity, which requires similar degree of the measurement data preprocessing for both types of sensors.

2 METHODOLOGY OF EXPERIMENTATION

2.1 Data Acquisition

The raw measurement data for experimentation have been acquired by means of the APDM Opal accelerometric sensor (*cf.* *http://www.apdm.com/wearable-sensors/*) attached to the waist of a monitored person, and by means of a pair of synchronised impulse-radar sensors – *cf.* (Morawski et al., 2014) – whose location is shown in figure 1. A monitored person has moved at the distance of *ca.* 1–6.5 m from each of them.

The walking velocity has been assessed on the basis of real-world data acquired when an experimenter has been walking at various constant velocities, ranging from 0.5 m/s to 1.0 m/s, forth and back along a straight line – $R = 20$ times along the x-axis, between points (0,3) and (4,3), and R times along the y-axis, between points (2,1) and (2,5) (*cf.* figure 1). In order to assure a known constant walking velocity, a metronome has been used.

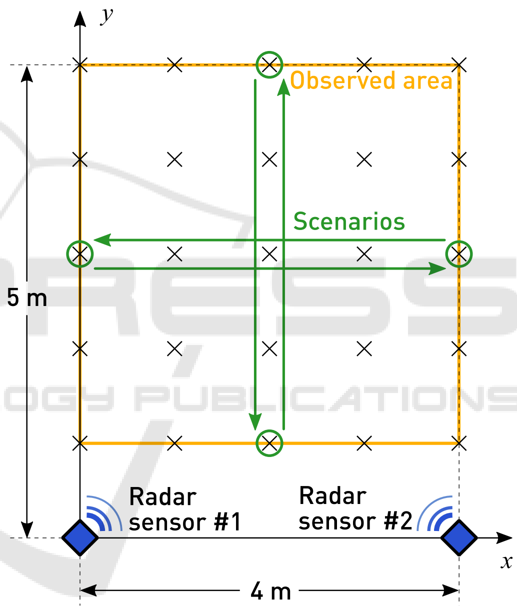

Figure 1: Experimental setup; the crosses indicate the reference points, *i.e.* the points where marks have been placed on the floor.

2.2 Data Preprocessing

2.2.1 Radar Data

The measurement data from a pair of impulse-radar sensors – after preliminary preprocessing, as described in (Miękina et al., 2016a) – take on the form of a sequence of numbers representative of the x-y coordinates of a monitored person.

A sequence of the estimates of the instantaneous walking velocity may be obtained by numerical differentiation of the sequence of the position estimates, *e.g.* by means of the central-difference method (Wagner et al., 2015), defined by the formula:

$$\hat{d}_n^{(1)} \equiv \frac{d_{n+1} - d_{n-1}}{\Delta t_n} \quad \text{for} \quad n = 1, \ldots, N-1 \qquad (1)$$

where $\{d_n\}$ is a sequence of data to be differentiated, and $\Delta t_n \equiv t_{n+1} - t_{n-1}$ are the differentiation steps, with t_n denoting the time moments at which the data have been acquired. That method is, however, very sensitive to errors corrupting the data used for derivative estimation; therefore, it should be regularised through, *e.g.*, optimisation of the differentiation step. The total velocity magnitude has been calculated according to the formula:

$$\hat{v}_n = \sqrt{\left(\hat{x}_n^{(1)}\right)^2 + \left(\hat{y}_n^{(1)}\right)^2} \quad \text{for} \quad n = 1, \ldots, N \qquad (2)$$

where $\hat{x}_n^{(1)}$ and $\hat{y}_n^{(1)}$ are estimates of the first derivatives, computed on the basis of the estimates of the *x*- and *y*-data sequences.

2.2.2 Accelerometric Data

An accelerometric sensor – composed of an accelerometer, magnetometer and gyroscope – provides a sequence of data representative of the monitored person's instantaneous acceleration in three directions, *viz.* magnetic north, magnetic west, and vertical. A sequence of the estimates of the instantaneous velocities in these directions can be obtained by numerical integration of the sequences of the acceleration values. It must be, however, taken into account that – since both systematic and random errors corrupting accelerometric data propagate through the integration process (Thong et al., 2004) – the velocity estimates may be subject to a growing-with-time drift and random errors whose standard deviation is also growing with time. As a consequence, non-zero estimates may appear even when a monitored person is standing still; therefore, the velocity estimates have to be corrected by means of a so-called zero-velocity compensation procedure (Bang et al., 2003). It can be applied to a velocity trajectory whose first and last values are known to be zero. In the research reported here, the following correction formula has been used:

$$\hat{v}_n \Leftarrow \hat{v}_n - \delta \frac{n - n_1}{n_2 - n_1} \quad \text{for} \quad n_1 < n < n_2 \qquad (3)$$

where $\delta = \hat{v}_{n_2} - \hat{v}_{n_1}$, n_1 and n_2 are the indices of the first and last time instants of the movement, respectively; the latter parameters have been determined experimentally. The corrected velocity trajectories in the magnetic north and west directions (denoted with $\hat{v}_n^N$ and $\hat{v}_n^W$, respectively) have been used for computing the total velocity magnitude according to the formula:

$$\hat{v}_n = \sqrt{\left(\hat{v}_n^N\right)^2 + \left(\hat{v}_n^W\right)^2} \quad \text{for} \quad n = 1, \ldots, N \qquad (4)$$

2.3 Criteria of Performance Evaluation

In each experiment, R sequences of the instantaneous total velocity estimates have been computed using equations 2 and 4 on the basis of both radar data and accelerometric data:

$$\left\{\hat{v}_n^{(r)} \mid n = 1, \ldots, N\right\} \quad \text{for} \quad r = 1, \ldots, R \qquad (5)$$

Prior to the evaluation of the uncertainty of the estimation, some outlying sequences have been removed to prevent the misinterpretation of the results. The outlying sequences have been identified as those whose mean value:

$$\hat{\mu}^{(r)} = \frac{1}{N} \sum_{n=1}^{N} \hat{v}_n^{(r)} \qquad (6)$$

deviated from the group mean value:

$$\hat{\mu} = \frac{1}{R} \sum_{r=1}^{R} \hat{\mu}^{(r)} \qquad (7)$$

by more than three standard deviations:

$$\hat{\sigma} = \sqrt{\frac{1}{R-1} \sum_{r=1}^{R} \left(\hat{\mu}^{(r)} - \hat{\mu}\right)^2} \qquad (8)$$

Next, the qualitative assessment of the uncertainty of the estimates has been performed. It has been based on the inspection of the estimates of the mean:

$$\hat{\mu}_n = \frac{1}{R'} \sum_{r=1}^{R'} \hat{v}_n^{(r)} \qquad (9)$$

and standard deviation:

$$\hat{\sigma}_n = \sqrt{\frac{1}{R'-1} \sum_{r=1}^{R'} \left(\hat{v}_n^{(r)} - \hat{\mu}_n\right)^2} \qquad (10)$$

of each element of the sequence of the instantaneous velocity estimates; R' denotes the number of sequences in a set under consideration after removing the outlying sequences.

Finally, the quantitative assessment of the uncertainty of the estimates of the mean walking velocity has been done using the following indicators:

- the absolute discrepancy between the mean value of the estimates of the velocity and the predefined value of that velocity,

- the absolute root-mean-square discrepancy of the estimates with respect to the predefined value,
- the lower and upper bounds of the absolute discrepancy between the estimates and the predefined value.

The above indicators have been calculated separately for each set of R' estimates of mean walking velocity, obtained in each experiment by averaging its N samples.

3 RESULTS AND DISCUSSION

In figures 2–5, the mean sequences of instantaneous velocity estimates of a moving person, obtained on the basis of the radar data and accelerometric data – for both directions of movement (*i.e.* along *x*-axis and along *y*-axis) and for all predefined velocity values – are presented.

It is worth being noticed that the uncertainty of estimation, based on radar data, is direction dependent: for the movement along the *x*-axis and predefined velocity values from 0.5 m/s to 0.7 m/s, the estimated mean value of the velocity oscillates around the predefined value during the movement. This cannot be observed for the movement along the *y*-axis in the same range of velocity values. Moreover, it may be seen that the standard deviation of the velocity is greater for the movement along the *x*-axis.

Those differences are caused by the fact, that the calculation of the position of the moving person is easier when the distance between the person and each of the radars is equal (*i.e.* when each radar *sees* the same side of the human body).

On the other hand, it may be noticed that the uncertainty of estimation, based on accelerometric data, is direction independent.

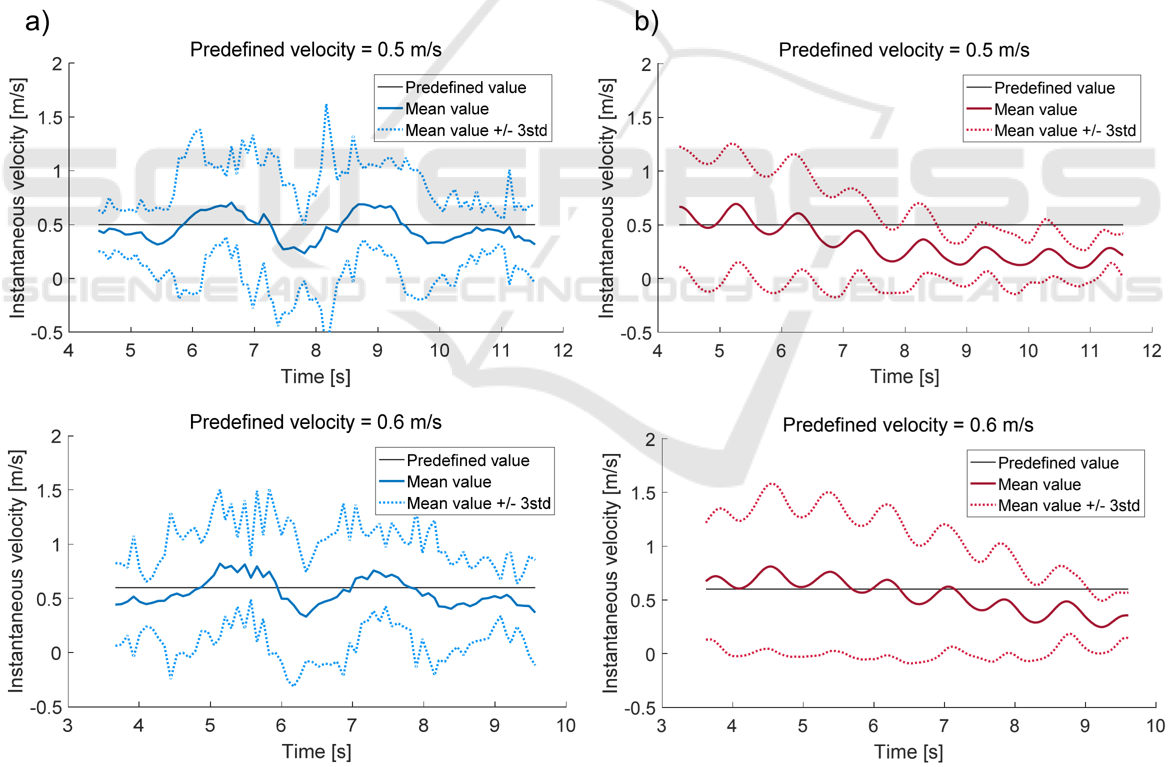

Figure 2: Uncertainty indicators determined for estimates of the velocity of a moving person, obtained on the basis of the radar data (a) and accelerometric data (b), for the movement along *x*-axis with the velocity values ranging from 0.5 m/s to 0.6 m/s. In all sub-figures: the thick solid line denotes the sequence of mean values, while the dotted lines – the sequences of values that are three standard deviations away from the mean sequence.

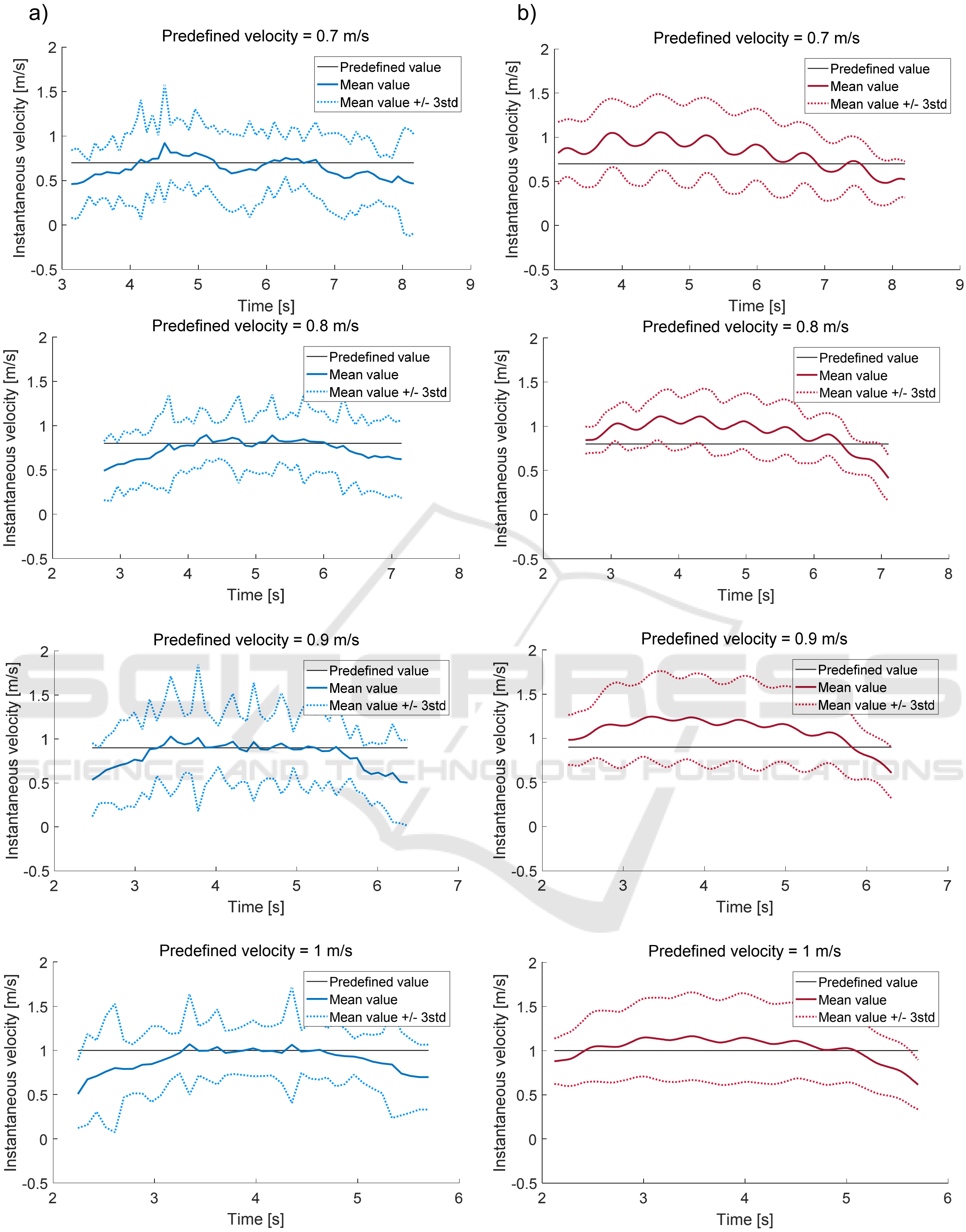

Figure 3: Uncertainty indicators determined for estimates of the velocity of a moving person, obtained on the basis of the radar data (a) and accelerometric data (b), for the movement along *x*-axis with the velocity values ranging from 0.7 m/s to 1.0 m/s. In all sub-figures: the thick solid line denotes the sequence of mean values, while the dotted lines – the sequences of values that are three standard deviations away from the mean sequence.

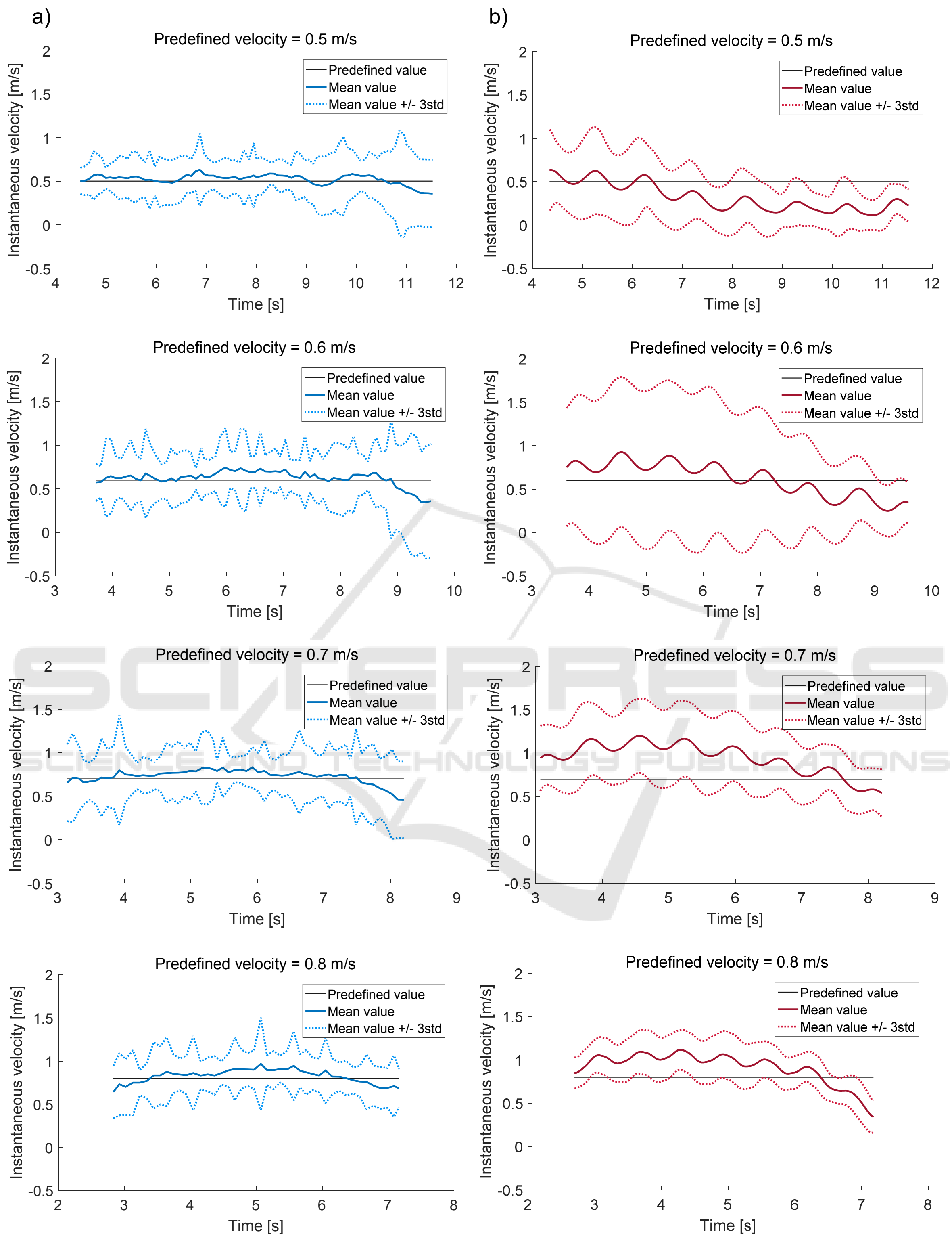

Figure 4: Uncertainty indicators determined for estimates of the velocity of a moving person, obtained on the basis of the radar data (a) and accelerometric data (b), for the movement along y-axis with the velocity values ranging from 0.5 m/s to 0.8 m/s. In all sub-figures: the thick solid line denotes the sequence of mean values, while the dotted lines – the sequences of values that are three standard deviations away from the mean sequence.

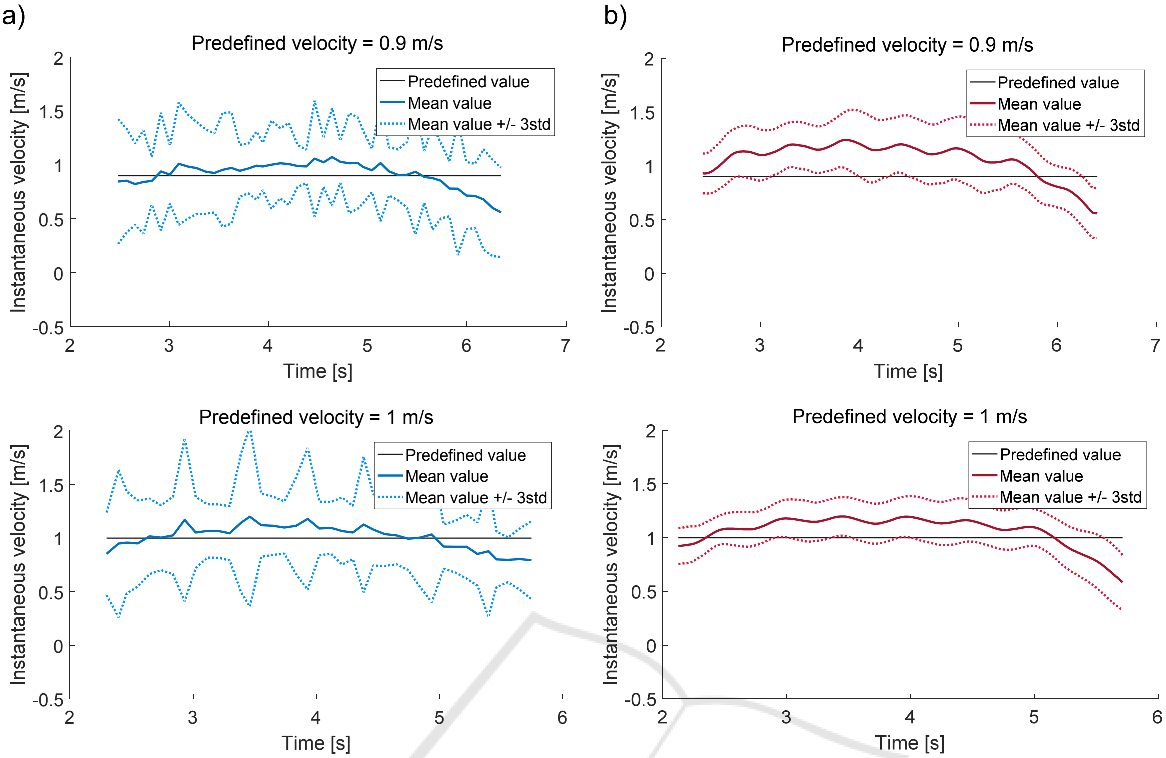

Figure 5: Uncertainty indicators determined for estimates of the velocity of a moving person, obtained on the basis of the radar data (a) and accelerometric data (b), for the movement along y-axis with the velocity values ranging from 0.9 m/s to 1.0 m/s. In all sub-figures: the thick solid line denotes the sequence of mean values, while the dotted lines – the sequences of values that are three standard deviations away from the mean sequence.

In figure 6, the so-called box plots representing the aggregated uncertainty of the estimation of the mean walking velocity, performed on the basis of the radar data and accelerometric data, for each investigated value of the walking velocity, are presented. Each box plot indicates:

- the median value;
- the interquartile range (IQR), *i.e.* range between the first and third quartile;
- the smallest value still within 1.5 IQR from the first quartile, and the largest value still within 1.5 IQR from the third quartile;
- the values lying outside 1.5 IQR from the first quartile and 1.5 IQR from the third quartile (marked with crosses).

In table 1 and table 2, the numerical results of all experiments – performed for various walking velocities – are collected.

The results presented in tables 1 and 2 show that the estimates of the mean walking velocity, obtained on the basis of the radar data, are far more accurate than those obtained on the basis of the accelerometric data. For the estimation of the velocity based on the radar data the mean discrepancy, *i.e.* the difference between estimated mean value and a predefined value of the velocity, varies from –0.12 to 0.03 m/s, while it varies from –0.18 to 0.24 m/s for the estimation based on accelerometric data. Moreover, it can be observed that the estimates obtained on the basis of the radar data are more concentrated around their mean values – the root-mean-square discrepancy of the radar-data-based velocity estimates varies from 0.02 to 0.12 m/s, while it varies from 0.08 to 0.27 m/s for the accelerometric-data-based estimates.

It can also be noticed that the estimates of the mean walking velocity, obtained on the basis of the radar data, tend to be underrated with respect to the predefined walking velocity for the movements along the x-axis, and very accurate for the

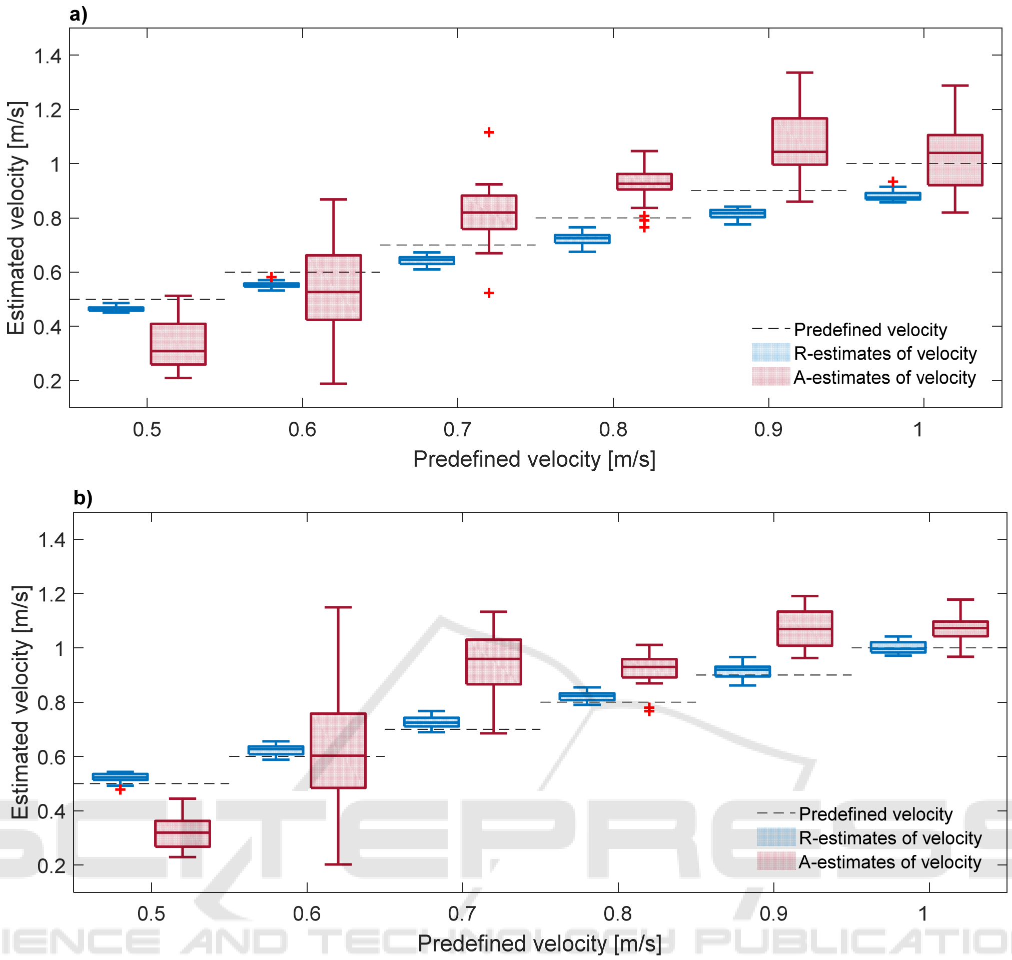

Figure 6: Box plots representing the uncertainty of the estimation of the walking velocity, based on the radar data (R-estimates) and accelerometric data (A-estimates); a) *x*-axis movement, b) *y*-axis movement.

movements along the *y*-axis. On the other hand, the estimates of the mean walking velocity, obtained on the basis of the accelerometric data, seem to be underrated for lower walking velocities and overrated for faster movements.

Lastly, it should be noted that the impact of the imperfections of the movements of the experimenter, reproducing the predefined patterns, are the same for both sensors; so, not changing the result of comparison.

4 CONCLUSIONS

The novelty of the study, whose results are presented in this paper, consists in systematic comparison of two monitoring techniques, *viz.* impulse-radar sensors and accelerometric sensors, when applied for healthcare-oriented characterisation of the human movements.

The performance of both types of sensors has been compared on the basis of data acquired by means of them in a series of real-world experiments which involved tracking of a person moving according to predefined patterns. The indicators of uncertainty of the velocity estimation have been determined with respect to the assumed predefined values of velocity.

Prior to the evaluation of the uncertainty, the measurement data from both types of sensors have to be adequately processed. The velocity estimates, obtained on the basis of the accelerometric data, are determined by numerical integration of the sequences of the acceleration estimates and corrected by means of a zero-velocity compensation procedure. The velocity estimates, obtained on the basis of the radar data, are determined using the regularised numerical differentiation of the sequence of the position estimates.

Table 1: Uncertainty of mean velocity estimation for the movement along *x*-axis.

Uncertainty indicators characterising estimates of mean velocity	Predefined walking velocity [m/s]					
	0.50	0.60	0.70	0.80	0.90	1.00
Impulse-radar sensors						
Mean discrepancy [m/s]	–0.03	–0.04	–0.06	–0.08	–0.08	–0.12
Root-mean-square discrepancy [m/s]	0.04	0.05	0.06	0.08	0.09	0.12
Upper bound of the discrepancy [m/s]	–0.01	0.01	–0.03	–0.03	–0.06	–0.07
Lower bound of the discrepancy [m/s]	–0.05	–0.07	–0.09	–0.13	–0.12	–0.14
Accelerometric sensors						
Mean discrepancy [m/s]	–0.17	–0.06	0.12	0.12	0.18	0.03
Root-mean-square discrepancy [m/s]	0.19	0.17	0.17	0.14	0.23	0.13
Upper bound of the discrepancy [m/s]	0.01	0.27	0.42	0.25	0.44	0.29
Lower bound of the discrepancy [m/s]	–0.29	–0.41	–0.18	–0.03	–0.04	–0.18

Table 2: Uncertainty of mean velocity estimation for the movement along *y*-axis.

Uncertainty indicators characterising estimates of mean velocity	Predefined walking velocity [m/s]					
	0.50	0.60	0.70	0.80	0.90	1.00
Impulse-radar sensors						
Mean discrepancy[m/s]	0.02	0.03	0.03	0.02	0.01	0.00
Root-mean-square discrepancy [m/s]	0.03	0.03	0.03	0.03	0.03	0.02
Upper bound of the discrepancy [m/s]	0.04	0.06	0.07	0.05	0.07	0.04
Lower bound of the discrepancy [m/s]	–0.02	–0.01	–0.01	–0.01	–0.04	–0.03
Accelerometric sensors						
Mean discrepancy [m/s]	–0.18	0.02	0.24	0.12	0.17	0.07
Root-mean-square discrepancy [m/s]	0.19	0.21	0.27	0.13	0.18	0.08
Upper bound of the discrepancy [m/s]	–0.06	0.55	0.43	0.21	0.29	0.18
Lower bound of the discrepancy [m/s]	–0.27	–0.40	–0.01	–0.03	0.06	–0.03

The experiments performed have demonstrated that impulse-radar sensors enable one to estimate the walking velocity more accurately than the accelerometric sensors. The estimates obtained on the basis of data from the latter sensors are affected by larger bias and are more widely spread around their mean values.

Since falls among elderly persons are the main cause of their admission and long-term stay in hospitals (Abbate et al., 2010), the systems for monitoring of elderly and disabled persons are expected to perform some functions related to fall prevention and/or fall detection. The functions related to fall prevention are implemented to overcome fall risk factors, implied by natural aging-related physical disabilities, and promptly indicate the increasing risk of falling; the functions related to fall detection are to reliably detect falls, when they occur, and minimise the potential injuries. Sensors used for fall prevention are expected to be accurate enough to enable the monitoring system to identify changes in the monitored person's health status on the basis of relatively slow and subtle changes in his/her gait characteristics, *e.g.* changes of the mean walking velocity. Sensors used for fall detection should be selected and optimised with respect to their sensitivity as to enable the monitoring system to detect short abrupt changes in person's velocity or acceleration.

In light of the results presented in this paper, the impulse-radar sensors seem to be promising means for reliable fall prevention since they enable the through-the-wall monitoring of persons (as the electromagnetic waves propagate through non-metal objects) and highly accurate estimation of their velocity; those sensors are, however, less appropriate for fall detection because of the relatively low rate of data acquisition. On the other hand, the accelerometric sensors appear to be not well-suited for the long-term monitoring of the person's gait characteristics, but better satisfy the requirements related to fall detection, due to their higher sensitivity, significantly higher rate of data acquisition, and suitability for outdoor use.

One may thus conclude that both types of sensors studied in this paper, *viz.* impulse-radar sensors and accelerometric sensors, are in some way complementary, and therefore the combined use of both of them may contribute to the increase in the reliability of the monitoring of elderly and disabled persons.

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