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Using accelerometers for evaluation of measurement uncertainty in impulse-radar system for monitoring of elderly and disabled persons

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***Abstract* – The importance of research on new technologies that could be employed in care services for elderly and disabled persons is highlighted. Advantages of radar sensors, when applied for non-invasive monitoring of such persons in their home environment, are indicated. Methods for estimation of the instantaneous velocity and the mean walking velocity (including automatic detection of time intervals when the person is in motion), on the basis of the measurement data from radar sensors and accelerometers, are described. A novel methodology for evaluation of the estimation uncertainty of the person's average walking velocity, in an impulse-radar-based system for monitoring of movements, is presented. The results of a series of real-world experiments, with a person moving at different predefined velocities, are shown. They are indicating that the accuracy of radar-data-based detection of the person's motion and estimation of person's walking velocity may be sufficient for some healthcare applications.**

***Keywords* – impulse radar, accelerometer, measurement uncertainty, velocity estimation, healthcare**

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 (*cf. http://www.healthy-life-years.eu/*). The problem of organised care over elderly and disabled persons is, therefore, of growing importance. Hence the demand for research on new technologies that could be employed in the systems supporting care services for such persons. The capabilities of those systems include, but are not limited to, non-invasive monitoring of the movements and vital bodily functions of persons in their home environment.

Recently, numerous attempts have been made to apply radar technology for monitoring of elderly and disabled persons [1–8]. Those attempts are mainly motivated by the conviction that these techniques may be less intrusive than vision-based solutions (*e.g.* digital cameras), less cumbersome than the wearable solutions (*e.g.* accelerometers and gyroscopes), and less invasive with respect to the home environment than the environmental solutions (*e.g.* pressure sensors).

One of the most attractive features of the radar-based systems is the possibility of the through-the-wall tracking of human activity, and therefore its monitoring in the whole area of the household without the need to install sensors in each room. Although the detailed analysis of the movements of a monitored person is not feasible if radar sensors are used as the only source of data, it is possible to apply them for estimation of his/her walking velocity which may help healthcare personnel to evaluate his/her health state.

In this paper, the measurement uncertainty of the persons' walking velocity estimation, in an impulse-radar system for monitoring of elderly and disabled persons, is investigated. This uncertainty is evaluated using the data acquired by means of the wearable accelerometers – the devices which by their principle of operation are more suitable for velocity estimation, and are used for this purpose in the majority of existing monitoring systems. The study is based on a series of real-world experiments which comprise simultaneous recording of the gait characteristics of the person moving according to a predefined pattern by means of both types of sensors and statistical analysis of measurement data acquired in this way.

II. LITERATURE OVERVIEW

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 [9–15]. Radar-based systems have been proposed for persons' monitoring including operations varying from walking velocity measurement to fall detection [16–18]. Caroppo *et al.* proposed in their 2015 paper [19] a system based on the fusion of data from radar sensors, depth sensors, and wearable accelerometers, allowing for long-term monitoring of elderly persons. The 2016 book chapter [20] 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 [21] 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. ALGORITHMS FOR VELOCITY ESTIMATION

A. Estimation of instantaneous velocity

In the systems based on impulse-radar sensors, the person's velocity can be estimated using data representative of the space coordinates of that person's position. A sequence of the estimates of the instantaneous velocity may be obtained by numerical differentiation of the sequence of the position estimates, *e.g.* by means of the central-difference method. The latter is, however, sensitive to errors corrupting the data used for derivative estimation; therefore, it should be regularised because the errors corrupting the position estimates resulting from radar data are not negligible [22]. If two radar sensors are used, the estimation of the instantaneous walking velocity comprises differentiation of the *x*- and *y*-data sequences separately, and calculation of the velocity magnitude according to the formula:

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

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.

If an accelerometer is used for monitoring, then the person's velocity can be estimated using data representative of that person's acceleration in the magnetic north and west directions, the data acquired by means of that sensor. 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 [23] – 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 the person is standing still; therefore, the velocity estimates have to be corrected by means of a so-called zero-velocity compensation procedure [24]. It can be applied to a velocity trajectory whose first and last values are known to be zero according to the formula:

$$v_n \Leftarrow v_n - \delta \frac{n - n_1}{n_2 - n_1} \quad \text{for} \quad n_1 < n < n_2 \tag{2}$$

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

$$v_n = \sqrt{\left(v_n^N\right)^2 + \left(v_n^W\right)^2} \quad \text{for} \quad n = 1, \ldots, N \tag{3}$$

B. Estimation of average walking velocity

An estimate of the average walking velocity can be obtained by averaging the v_n values over the periods in which the monitored person is walking. For this purpose, an algorithm for automatic detection of motion is proposed which is comparing the distance, travelled in a given period of time, T, with a given threshold, ϑ. A binary sequence, indicating motion, is computed according to the formula:

$$b_n \equiv \begin{cases} 1 & \text{if} \quad d_n > \dfrac{t_n - t_{n_0}}{T} \vartheta \\ 0 & \text{otherwise} \end{cases} \quad \text{for} \quad n = 1, \ldots, N \tag{4}$$

where:

$$d_n \equiv \sum_{\nu = n_0}^{n} \sqrt{\left(x_\nu - x_{\nu-1}\right)^2 + \left(y_\nu - y_{\nu-1}\right)^2} \tag{5}$$

$$n_0 \equiv \arg_\nu \inf \left\{ \nu ; t_\nu \geq t_n - T, \nu = 0, \ldots, n-1 \right\} \tag{6}$$

The values of T and ϑ should be empirically optimised to prevent small deviations in the position – caused, for example, by the inability of the monitored person to be perfectly motionless, or by the movement of his/her limbs – from being considered as motion.

To smooth the sequences at the output of the motion detection algorithm, the morphological opening and closing filters are applied [25]. Moreover, to avoid underestimation of the average velocity, only the periods in which the instantaneous velocity is almost constant are taken into account; therefore, the periods, in which the monitored person is accelerating or decelerating, are ignored by using morphological erosion. The average walking velocity is calculated in the time intervals determined in this way.

In the research reported here, the values of the parameters have been set to $T = 0.35\,\mathrm{s}$ and $\vartheta = 0.1\,\mathrm{m}$; those values – chosen experimentally to yield the best overall results – correspond to the minimal detectable velocity of *ca.* $v = 0.3\,\mathrm{m/s}$. As long as the ratio ϑ / T is preserved, the results of the motion detection do not vary considerably. Nevertheless, the experiments have shown that a longer window of analysis may result in longer motion intervals (including the periods of person's acceleration and deceleration), and thus may lead to larger velocity underestimation. On the other hand, a shorter window of analysis may result in the detection of many brief motions, since – as it can be seen in Fig. 1 and Fig. 2 – the instantaneous velocity estimates may vary and momentarily assume values lower than the defined threshold.

In Fig. 1, an exemplary sequence of the estimates of the instantaneous velocity is presented along with the time interval during which the person's motion has been detected. The subsequent averaging of the velocity is performed over that time interval.

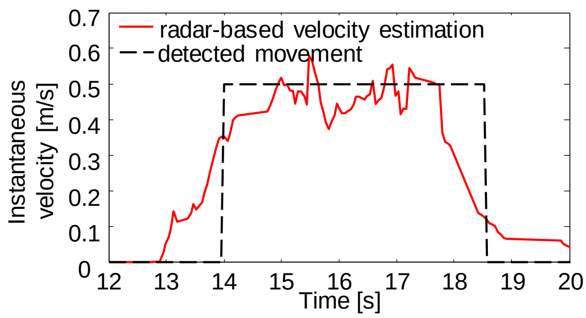

Fig. 1. Estimates of the instantaneous velocity, obtained on the basis of the radar data, and a result of motion detection; the predefined velocity = 0.5 m/s.

IV. METHODOLOGY OF EXPERIMENTATION

The key idea of this paper is a novel methodology for evaluation of the measurement uncertainty of the person's walking velocity in a monitoring system based on impulse-radar sensors. It is proposed to use the reference data acquired by means of accelerometers, *i.e.* the devices being by the principle of operation more suitable for the velocity estimation, and used for this purpose in the majority of existing monitoring systems.

A use of non-standard approach of experimentation is implied by the problematic nature of the measurand itself, *i.e.* the velocity-like quantity measured by means of impulse-radar sensor. A human body has a considerable volume and generates complex echoes which cannot be attributed to any specific point of that body (*e.g.* to *plexus solaris*); therefore, the resulting estimates of its position trajectories are prone to sudden variations caused by, *e.g.*, the changes in the body orientation or arms sways. As a consequence, the estimates of the velocity trajectories – resulting from numerical differentiation of the sequences of the position estimates – also cannot be associated with any specific point of that body. That is why the reference values are inaccessible, and therefore some uncertainty indicators, such as systematic errors, cannot be evaluated.

Accelerometers are extensively used in the research on monitoring of human movements, including fall detection [26–46]. Those devices are widely available, easy to use, and can be utilized to alleviate the lack-of-reference problem described. Since an accelerometer can be attached to any arbitrary point on a human body (*e.g.* the middle of the persons' waist), the device's readings can be associated with that particular point and can be further treated as a reference – it can be assumed that velocities of all the other body parts cannot deviate much from the velocity of the reference point.

The reported study comprises a series of real-world experiments during which the data representative of the behaviour of a monitored person, moving with a predefined velocity, have been simultaneously recorded by both types of sensors. In particular, the data representative of walking forth and back along a straight line – 4 times, on the distance of 3 meters at different predefined velocity values – have been recorded. In order to assure a known constant walking velocity, a metronome has been used; the accelerometric data have been acquired by means of the APDM Opal device [47].

The sequences of the estimates of the instantaneous velocity of the monitored person, obtained on the basis of data, acquired by means of both sensors, have been compared taking into account their mean values and standard deviations. Moreover, the root-mean-square discrepancy, as well as the lower and the upper bounds of the absolute discrepancy of the estimates of instantaneous velocity, obtained on the basis of the radar data, have been estimated with respect to the estimate of the mean velocity value obtained on the basis of the accelerometric data. It has to be noted, though, that the worst-case uncertainty, expressed in this way, is a composition of uncertainties related to the radar-based and accelerometer-based estimation of the velocity – including processing of measurement data.

V. RESULTS AND DISCUSSION

In Fig. 2, exemplary sequences of instantaneous velocity of a moving person, obtained on the basis of the data from the radar sensors and from accelerometers, are presented; during this experiment, the predefined walking velocity has been 0.7 m/s. Furthermore, in Table 1, the numerical results of all experiments – performed for different walking velocities – are collected.

Table 1. Results of experimentation.

Uncertainty indicators characterising estimates of instantaneous velocity	Predefined walking velocity [m/s]					
	0.50	0.60	0.70	0.80	0.90	1.00
Evaluation of accelerometer-based velocity estimation						
Mean value – predefined walking velocity [m/s]	−0.10	0.00	0.01	0.23	−0.01	0.13
Standard deviation [m/s]	0.15	0.14	0.12	0.17	0.12	0.14
Evaluation of radar-based velocity estimation						
Mean value – predefined walking velocity [m/s]	−0.09	−0.09	−0.12	−0.08	−0.05	−0.20
Standard deviation [m/s]	0.09	0.20	0.26	0.46	0.37	0.37
Evaluation of radar-based velocity estimation with respect to accelerometer-based mean velocity						
Root-mean-square discrepancy [m/s]	0.09	0.22	0.30	0.55	0.37	0.49
Upper bound of the absolute discrepancy [m/s]	0.18	0.85	0.72	1.57	0.83	0.62
Lower bound of the absolute discrepancy [m/s]	−0.30	−0.48	−0.66	−0.94	−0.68	−1.10

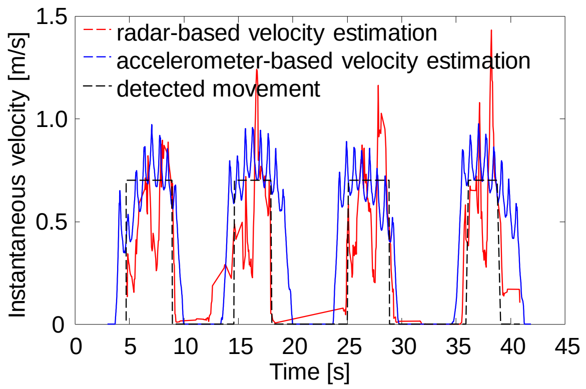

Fig. 2. Sequences of instantaneous velocity of a moving person, obtained on the basis of the measurement data from radar sensors and accelerometers; the predefined velocity = 0.7 m/s.

It can be observed in Fig. 2 that the estimates of instantaneous velocity, obtained on the basis of radar data, quite accurately follow the pattern of the time intervals when the monitored person has been in motion. In this experiment, the mean walking velocity, estimated on the basis of the radar data, has been 0.58 m/s, while the mean walking velocity, estimated on the basis of the accelerometric data, has been 0.71 m/s; thus, the former are slightly underscored. Moreover, the velocity estimates obtained on the basis of radar data tend to vary much more than those obtained by means of the accelerometer used as the reference values: the standard deviation of the radar-based velocity estimates has reached 0.26 m/s while the standard deviation of the accelerometer-based velocity estimates has been 0.12 m/s. Finally, as it has been observed, the root-mean-square discrepancy of the velocity estimates, obtained on the basis of radar data, has been 0.30 m/s, while the lower and upper bounds of the absolute discrepancy of the estimates have been −0.66 m/s and 0.72 m/s, respectively. The results presented in Table 1 seem to confirm the expectation that, on the whole, the estimates of the mean walking velocity, obtained on the basis of the accelerometric data, quite accurately reflect the predefined velocity. It has to be noted that the noticeable overestimation of the walking velocity assumed to be 0.8 m/s has been identified as a result of an unexpected abrupt movement of the performer during the experiment. In all experiments, the standard deviation of the estimates of the instantaneous velocity, obtained on the basis of the accelerometric data, has been at the same level. Further, it can be observed that the mean walking velocity, estimated on the basis of the radar data, has been generally underscored with respect to the mean walking velocity, estimated on the basis of the accelerometric data; in the worst-case scenario, the mean velocity has been underestimated by 0.33 m/s. It can also be noticed that the standard deviation of the estimates of the instantaneous velocity, obtained on the basis of radar data, has assumed larger values for faster movements (walking velocities of 0.8–1.0 m/s); this could have resulted from the vigorous movements of the body making the processing of measurement data more challenging.

VI. CONCLUSIONS

The novelty of the study, reported in this paper, consists in a methodology for evaluation of the measurement uncertainty of the person's walking velocity in a monitoring system based on the impulse-radar sensors, *viz.* the methodology based on the use of the reference data acquired by means of the accelerometers. This non-conventional approach is implied by the problematic nature of the measurand and the lack of the reference values that could be used in experimentation.

Prior to the evaluation of the uncertainty, the measurement data from both considered types of the 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 and averaged over automatically detected time intervals when the person is in motion.

The experiments performed have shown that the estimates of the mean walking velocity, obtained on the basis of the radar data, have been generally underscored with respect to the estimates obtained on the basis of the accelerometric data – in the worst-case scenario, the mean velocity has been underestimated by 0.33 m/s. Moreover, the standard deviation of the estimates of the instantaneous velocity, obtained on the basis of the radar data, has assumed larger values for faster movements.

As suggested in the literature, *e.g.* [48], the walking velocity lower than 0.6 m/s enables one to predict an increase in the risk of falls and hospitalisation of a monitored person. Moreover, an improvement in walking velocity of at least 0.1 m/s is a useful predictor for well-being, while a decrease of the same amount is correlated with poorer health status, greater disability, longer hospital stays, and increased medical costs. That is why the development of the accurate algorithms for estimation of walking velocity in the impulse-radar systems for monitoring of elderly and disabled persons is of crucial importance.

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