Comparison of three least-squares methods for fusion of data from radar and depth sensors applied for persons’ monitoring

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**Abstract.** The research reported in this paper is related to the fusion of measurement data from the impulse-radar sensors and infrared depth sensors applied in a system for unobtrusive monitoring of elderly persons. Three least-squares methods – ordinary least squares, total least squares and weighted total least squares – used for fusion of measurement data are compared with respect to their capacity of decreasing the uncertainty of position estimation in a series of experiments which involved the tracking of a moving person.

**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 persons. These systems are expected to detect dangerous events, such as person’s fall, but also to predict those events on the basis of acquired data [1, 2]; it has been shown recently that the analysis of gait may contribute to the fall prevention [3, 4].

There are three main categories of monitoring techniques already applied in healthcare practice – vision-based, environmental, and wearable. There are also two emerging categories: radar-based and depth-sensor-based techniques; they seem to be especially suitable for the monitoring of elderly persons because they are less intrusive than vision-based techniques, less cumbersome than the wearable techniques, and less invasive with respect to the home environment than the environmental techniques [5].

Radar sensors and depth sensors operate according to different physical principles and, therefore, have specific complementary advantages and disadvantages: radar sensors offer a broad field of view and capacity of the through-the-wall monitoring, but have relatively low accuracy; on the other hand, the depth sensors have higher accuracy, but their coverage is limited, and they cannot detect occluded targets. Taking into account the reliability theory, one may expect that the combination of such sensors, followed by adequate data fusion, could be beneficial.

The research reported in this paper is a significant development of the work initiated in [6]: new methods for fusion of data from impulse-radar sensors and depth sensors, are presented, and their capacity of decreasing the uncertainty of the position estimates, acquired in a monitoring system based on both types of sensors, is compared.
2. Compared methods of data fusion

In the considered monitoring system, the impulse-radar sensors and depth sensors are independent sources of the estimates of the position of a monitored person; sequences of such estimates are fused according to the procedure comprising:

- the temporal ordering of the estimates from both sensors;
- the approximation of the sequence of ordered estimates \( \{ \tilde{x}_n | n = 1, \ldots, N \} \) by means of a linear combination of \( K \) linearly independent functions:
  \[
  \hat{f}(v; p) = \sum_{k=1}^{K} p_k \varphi_k(v)
  \]
  with \( \varphi_k(v) \) being the \( \text{sinc}(v) \) function shifted by \( n_k \) sampling intervals, and \( p = [p_1 \ldots p_K]^T \) – a vector of parameters to be estimated using one of the compared least-squares methods;
- the definition of the result of fusion as \( \{ \hat{x}_n \} := \{ \hat{f}(v_n; \hat{p}) | n = 1, \ldots, N \} \), where \( \hat{p} \) denotes the obtained estimate of the vector of parameters.

2.1. Method based on ordinary least-squares estimator (OLS)

The OLS method consists in the minimization of the following criterion [7]:

\[
J_{\text{OLS}}(p) = \| \tilde{x} - \Phi p \|_2^2
\]

where \( \tilde{x} = [\tilde{x}_1 \ldots \tilde{x}_N]^T \), \( \Phi = [\varphi_1 \ldots \varphi_K] \), and \( \varphi_k = [\varphi_k(v_1) \ldots \varphi_k(v_N)]^T \).

2.2. Method based on total least-squares estimator (TLS)

In contrast to the OLS method, this method minimizes the sum of squared orthogonal distances from the data points to the fitting line; it is based on the minimization of the criterion [7]:

\[
J_{\text{TLS}}(p) = \frac{\| \tilde{x} - \Phi p \|_2^2}{1 + \| p \|_2^2}
\]

2.3. Method based on weighted total least-squares estimator (WTLS)

Under the assumption that errors corrupting the data are not correlated, the fusion of the position estimates can be performed using the WTLS method based on the minimization of the criterion [7]:

\[
J_{\text{WTLS}}(p) = (\tilde{x} - \Phi p)^T \text{diag}^{-1}\{\sigma_1^2, \sigma_2^2, \ldots, \sigma_N^2\} (\tilde{x} - \Phi p)
\]

where \( \sigma_n^2 \) are the estimates of the variances of the random measurement errors, obtained experimentally during the calibration of the sensors.

3. Methodology of experimentation

The methodology of experimentation has followed the pattern described in [5, 6]. The measurement data for experimentation have been acquired by means of a pair of impulse-radar sensors and a single depth sensor; the relative configuration of the sensors and the monitored area is presented in figure 1.

In the experiments, a person has walked forth and back along ten predefined straight-line trajectories, viz. five trajectories along \( x \)-axis with various constant values of the \( y \)-coordinate and five analogous trajectories along \( y \)-axis; for each trajectory, twenty walks have been performed.

The uncertainty of the position estimates has been assessed according to a methodology proposed by the authors in [6]. For each trajectory, the absolute errors, corrupting the position estimates, have been calculated and assigned to the closest reference points (see figure 1); then, for each reference point, the so-called error ellipse, indicating the 99% confidence areas of the position estimates, has been determined. Quantitative assessment of the uncertainty of position estimation has been based on
the following uncertainty indicators: the mean norm of the error vector (i.e., vector obtained for each reference point, whose scalar components are equal to mean absolute errors of the position estimates being the closest to this reference point) and the mean area of the error ellipse.

In figure 2, the movement trajectories and corresponding error ellipses, obtained on the basis of radar data and depth data, are presented.

4. Results and discussion

In figure 3, the error ellipses indicating the 99% confidence interval of the position estimates, obtained on the basis of data fused by means of the compared least-squares methods, are presented; table I contains the values of the corresponding uncertainty indicators.

It can be seen that the smallest values of the uncertainty indicators have been obtained for the WTLS method; moreover, in almost all cases, those values, are smaller than the values calculated on the basis of radar data or depth data alone. Only in the case of $y$-coordinate = 1, the performance of the fusion is slightly worse than the performance of the depth sensor: in this area the variances of the
Table 1. Uncertainty of the position estimation.

| y = 5 m | Radar data | Depth data | OLS | TLS | WTLS |
|---------|------------|------------|-----|-----|------|
| mean norm of the error vector [m] | 0.27 | 0.14 | 0.16 | 0.16 | 0.12 |
| mean area of the error ellipse [m²] | 1.37 | 0.12 | 0.36 | 0.37 | 0.08 |

| y = 4 m | Radar data | Depth data | OLS | TLS | WTLS |
|---------|------------|------------|-----|-----|------|
| mean norm of the error vector [m] | 0.14 | 0.08 | 0.08 | 0.08 | 0.06 |
| mean area of the error ellipse [m²] | 0.30 | 0.10 | 0.10 | 0.10 | 0.04 |

| y = 3 m | Radar data | Depth data | OLS | TLS | WTLS |
|---------|------------|------------|-----|-----|------|
| mean norm of the error vector [m] | 0.06 | 0.06 | 0.06 | 0.06 | 0.04 |
| mean area of the error ellipse [m²] | 0.10 | 0.08 | 0.06 | 0.06 | 0.05 |

| y = 2 m | Radar data | Depth data | OLS | TLS | WTLS |
|---------|------------|------------|-----|-----|------|
| mean norm of the error vector [m] | 0.09 | 0.08 | 0.08 | 0.08 | 0.09 |
| mean area of the error ellipse [m²] | 0.08 | 0.07 | 0.05 | 0.06 | 0.06 |

| y = 1 m | Radar data | Depth data | OLS | TLS | WTLS |
|---------|------------|------------|-----|-----|------|
| mean norm of the error vector [m] | 0.22 | 0.04 | 0.13 | 0.13 | 0.06 |
| mean area of the error ellipse [m²] | 0.29 | 0.09 | 0.13 | 0.14 | 0.10 |

Errors are similar for radar data and depth data (resulting in similar weights of the estimates), but radar-based estimates have larger bias. However, in this case only three reference points have been taken into account since two extreme points have been located outside the field of view of the depth sensor.

5. Conclusions

The novelty of the research results, presented in this paper, consists in identification of the effectiveness of three least-squares methods for fusion of data from impulse-radar sensors and depth sensors, when applied for unobtrusive monitoring of elderly persons in their home environment.

The performed experiments have demonstrated that the smallest values of the uncertainty indicators may be obtained for the WTLS method which takes into account the uncertainty of the position estimates delivered by the sensors, viz. the variances of those estimates which may be obtained experimentally during the calibration of the sensors.

Further work will be focused on the assessment of the performance of more advanced methods of data fusion when applied not only to the estimation of the position of monitored person but also of other healthcare-related quantities, such as mean walking velocity.

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