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An optimized Kalman filter for the estimate of trunk orientation from inertial sensors data during treadmill walking

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ABSTRACT

The aim of this study was the fine tuning of a Kalman filter with the intent to provide optimal estimates of lower trunk orientation in the frontal and sagittal planes during treadmill walking at different speeds using measured linear acceleration and angular velocity components represented in a local system of reference.

Data were simultaneously collected using both an inertial measurement unit (IMU) and a stereophotogrammetric system from three healthy subjects walking on a treadmill at natural, slow and fast speeds. These data were used to estimate the parameters of the Kalman filter that minimized the difference between the trunk orientations provided by the filter and those obtained through stereophotogrammetry. The optimized parameters were then used to process the data collected from a further 15 healthy subjects of both genders and different anthropometry performing the same walking tasks with the aim of determining the robustness of the filter set up.

The filter proved to be very robust. The root mean square values of the differences between the angles estimated through the IMU and through stereophotogrammetry were lower than 1.0° and the correlation coefficients between the corresponding curves were greater than 0.91.

The proposed filter design can be used to reliably estimate trunk lateral and frontal bending during walking from inertial sensor data. Further studies are needed to determine the filter parameters that are most suitable for other motor tasks.

1. Introduction

The use of accelerometers to detect and quantify human motion has been considered for many years [1]. More recently, the use of this type of sensor to collect movement data has increased rapidly [2]. Modern "inertial measurement units" (IMUs) are small and self contained, enabling their use for extended periods outside the confines of a laboratory.

Previous studies have outlined the potential for simple IMUs to determine gross body motion as a means to quantify differences in activities of daily living [3]. Other studies have used IMUs to calculate inter-segment forces and moments [4] as well as spatial [5] and temporal [6] features of gait.

Accelerometers can be used as inclinometers when accelerations are small [7], however once accelerations increase the use of accelerometers alone is limited. This restriction can be overcome by the addition of other devices such as angular rate sensors [8]. These devices, however, are subject to drift over time which may jeopardize the time integration of their output signals while estimating orientation data [9]. This problem can be overcome by using recursive filters, such as complementary [10] or Kalman filters [11]. The latter choice is widely adopted in human movement analysis [9,12–17] motions such as head orientation [8], forearm motion [9,17,18], and lifting crates [17]. The benefits of having the filter act adaptively to account for the differing relative importance of the signals during periods of low or high acceleration have also been noted [8,19]. Currently, many commercially available IMUs have algorithms available that use a Kalman filter to convert the sensor measurements into information about the kinematic state (i.e. the orientation in space) of the device. These algorithms use parameters based on the characteristics of the sensors, such as the noise of the signal measured during static conditions [18]. Little has been reported detailing the implementation of a filter for the estimate of trunk orientations during walking and to assess the effects of altering its parameters.

The purposes of this study are: (a) to design a Kalman filter for the estimate of the lower trunk orientation during walking using accelerometer and gyroscope data; (b) to determine, through a sensitivity analysis, the importance of selecting the correct

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parameters for the Kalman filter to obtain accurate trunk orientations when walking on a treadmill at different speeds.

2. Materials and methods

2.1. Subjects and data collection

A total of 18 subjects (10 male, 8 female, age range 24–64) volunteered for the study. The subjects' self selected ''natural'' walking speed was determined by measuring the time it took them to cover a distance of 10 m walking along a straight, level path. An IMU (Freesense, Sensorize srl) was then secured to the lower back of the subjects using an elastic belt so that the unit local frame (ULF) axes were aligned with the anatomical axes of the lower trunk. In addition, three 15 mm diameter retro-reflective markers were attached to the unit case and defined a marker-cluster local frame (MLF).

Subjects were asked to perform three walking trials on a motorized treadmill. Trials were performed at natural walking speed, 80% of natural speed and 120% of natural speed, and each of them lasted 40s. Acceleration and angular velocity data were collected from the IMU (fs = 100 samples/s) while the marker trajectories were tracked by five infrared cameras (MX, Vicon, fs = 100 samples/s).

Pitch and roll angles, describing the orientation of the ULF were estimated from the IMU data using the Kalman filter as illustrated below and those describing the orientation of the MLF were reconstructed using photogrammetric data. The time-invariant offset of the MLF orientation relative to the ULF orientation was mathematically removed through a rigid transformation while the subject was standing still. In this way both instruments could be assumed to provide pitch and roll angles of the same lower trunk anatomical frame. The axial rotation of the trunk was not investigated in this study, since the yaw angle could not be estimated from the available IMU data.

In order to synchronise the two measuring systems' data, the subjects were asked to perform a forward bending of the trunk at the beginning and end of the walking trials, and the signals were aligned using the corresponding peaks in the pitch angles.

2.2. Kalman filter implementation

The Kalman filter [14] is used to estimate the state of a system, which, for an IMU, is represented by its orientation, defined as the rotation of the ULF relative to another frame attached to earth. The implementation of the filter for a system using accelerometers and gyroscopes is described in detail in Supplementary material.

To run the filtering procedure, initial estimates of the noise associated with the accelerometer (R^0) and gyroscope (Q^0) measurements are needed. Bench trials were performed to record the sensor signals in six different positions, in which the positive and negative x, y and z axes of the accelerometers, were each made to coincide with the gravity acceleration. These trials showed that Q^0, and R^0 can be considered constant in all three directions. They were hence expressed as: $Q^0 = q \cdot I$ and $R^0 = r \cdot I$, with I being a 3×3 identity matrix, and q and r being two parameters that need to be set to run the process. Furthermore, the relevant contribution of R^0 and Q^0 to the computation of the estimate of the state must be established. This can be done using the following reliability criteria: if the system is in a ''quasi static'' state [20] the magnitude (a) of the vector Acc must satisfy the following condition:

$$g - s_1 < a < g + s_2,$$

where g is the magnitude of the gravity acceleration vector, and s_1 and s_2 are two constants. If the above constraints are satisfied, the accelerometer signals are considered more reliable than the gyroscope signals and a higher relevance given to R^0. Otherwise, more reliability is placed on the gyroscope signals and a higher relevance given to Q^0.

To implement the above criteria, the matrix Q^i, representing the noise in the gyroscope data at any instant i, can be kept constant (and equal to Q^0), while the matrix R^i, representing the noise in the accelerometer data at any instant i, can be increased or decreased by a multiple of R^0 through a weighting coefficient w ($R^i = w \times R^0$), which is changed according to the values of s_1 and s_2. In this study, we chose to represent the relationship between w and s_1 and s_2 through a ramp function, defined as:

$$w = s_1 \quad \text{for } a \leq g - s_1,$$

$$w = m\frac{a - a_1}{s_2 - s_1}, \quad \text{for } g - s_1 < a < g + s_2,$$

$$w = s_2 \quad \text{for } a \geq g + s_2,$$

In summary, in order to run the above described Kalman process, the values of five parameters must be set: q, r, s_1, s_2 and m. On the basis of the previously described bench trials and on the authors experience, the following first approximation values were selected:

$$q = 1\mathrm{e}^{-8\circ}/\mathrm{s} \ \ \text{(static gyroscope signal noise)}$$

$$r = 1\mathrm{e}^{-8} \ \mathrm{m/s^2} \ \ \text{(static accelerometer signal noise)}$$

$$s_1 = 0.5 \ \mathrm{m/s^2}$$

$$s_2 = 0.05 \ \mathrm{m/s^2}$$

$$m = 200$$

2.3. Optimization procedure

Data from nine trials recorded from three randomly selected subjects at three different speeds were used to run the optimization procedure. Orientation angles for the IMU (pitch P_K and roll R_K) were calculated using the described Kalman filter with the first approximation parameters listed above. These angles were then compared to the corresponding angles calculated from the stereophotogrammetric data (pitch P_S and roll R_S). The root mean square of the differences between P_K and P_S (RMS_P) and between R_K and R_S (RMS_R) was then calculated along with the correlation coefficients (r_P and r_R, respectively) between the same angle time histories. Mean root mean square (RMS = mean(RMS_P, RMS_R)) and mean correlation coefficient (*corr* = mean(r_P, r_R)) were then computed.

The PatternSearch algorithm (Matlab®, Mathworks, Natick, MA) [21] was used to determine the optimum combination of parameters (q, r, s_1, s_2 and m) that minimized the quantity $J = \mathrm{RMS}_P/r_P + \mathrm{RMS}_R/r_R$. The optimization procedure was repeated three separate times, once for each of the slow, natural, and fast speed trials. The corresponding RMS and r values were computed as the mean of the corresponding values for the data of the three subjects The combination of parameters that gave the lowest J was finally selected as the optimal solution.

2.4. Sensitivity analysis

Once the optimized parameters were found, a sensitivity analysis was performed to assess their role in determining the final results. The Kalman filter was run by using the 3125 (5^5) combinations obtained by multiplying the optimal q, r, and m values by 1/50, 1/5, 1, 5, and 50 and the optimal s_1 and s_2 values by 1, 50, 100, 500 and 1000.

The analysis of the relevant results was divided into two steps. First the effects of the variation of the product $r \cdot m$ (representing the accelerometer noise for a non adaptive filter) and of q have been investigated. Second, the subsets of the combination of these values that provided the best results were used for investigating the effects of varying s_1 and s_2, which are the parameters that make the filter adaptive.

2.5. Filter accuracy assessment

The accuracy of the pitch and roll estimates obtained from the IMU data using the Kalman filter was assessed by comparing the data recorded in the 45 trials not used in the optimization process to those measured with the stereophotogrammetric system. Again, RMS and *corr* were used to this purpose, together with the offset values (computed as the difference between the mean values of the corresponding angles).

It should be noted that the stereophotogrammetric errors [22] propagate to the angles of interest in this study causing a maximal inaccuracy of 0.5°.

3. Results

Results relevant to the optimization procedure are shown in Table 1. The use of the approximation parameters led to an improvement in the estimate of about 2° when compared to the data obtained without using the filter. The residual error values, however, were still unsatisfactory, with a RMS of about 4–5° and correlation coefficients around 0.5 for the pitch and around 0.4 for the roll estimate.

The optimisation procedure produced an evident reduction of the RMS differences between the stereophotogrammetry and the Kalman angles (to less than 1°) and an increase of the mean correlation coefficients *corr* to values greater than 0.9. The best results were obtained for the natural speed trials. The corresponding values of the Kalman filter parameters were: q = 2.4e−007°/s, r = 1.61e−006 m/s², s_1 = 0.11 m/s², s_2 = 0.10 m/s², m = 80, and the corresponding J was 1.46°. Similar values were found in the other experimental conditions.

Fig. 1 shows the variability of the cost function index J as a function of the two parameters q and $r \cdot m$. As highlighted in the figure, very low values of J (black points) could be obtained not only for the optimum values of the parameters, but also for other combinations, all characterized by having a similar ratio $(r \cdot m)/q$

Table 1
Results of the optimization procedure.

Trial type	Filter	Pitch			Roll		
		RMS (°)	*corr*	Offset (°)	RMS (°)	*corr*	Offset (°)
Slow	Without filter	6.1 (1.2)	0.41 (0.32)	2.6 (0.6)	5.2 (1.2)	0.19 (0.34)	1.4 (0.4)
	First approximation parameters	4.7 (4.9)	0.53 (0.25)	2.9 (0.8)	3.6 (2.8)	0.39 (0.36)	1.6 (0.7)
	Optimized parameters	0.7 (0.4)	0.98 (0.01)	1.8 (0.7)	0.8 (0.2)	0.91 (0.03)	2.4 (0.4)
Natural	Without filter	7.1 (1.1)	0.41 (0.6)	2.8 (0.6)	6.2 (1.3)	0.09 (0.21)	1.5 (0.6)
	First approximation parameters	5.2 (2.2)	0.56 (0.05)	2.8 (0.7)	3.9 (0.3)	0.26 (0.05)	1.5(0.5)
	Optimized parameters	0.6 (0.4)	0.99 (0.01)	2.9 (0.5)	0.5 (0.1)	0.95 (0.01)	1.5 (0.6)
Fast	Without filter	7.7 (1.6)	0.32 (0.16)	2.7 (0.5)	7.6 (1.2)	−0.02 (0.21)	1.6 (0.4)
	First approximation parameters	5.4 (1.8)	0.49 (0.02)	2.8 (0.7)	5.2 (5.9)	0.13 (0.4)	1.5 (0.4)
	Optimized parameters	0.7 (0.1)	0.98 (0.01)	3.3 (0.4)	0.7 (0.4)	0.92 (0.02)	1.2 (0.3)

(with its values being equal to 544 ± 26 in the trials with $J < 2$). This means that if one of the parameters is varied, the other must vary as well in a proportional manner.

Fig. 2 shows the values of J obtained varying the parameters s_1 and s_2 for any combination of the parameters q, r, and m that gave the best results. Most of the solutions leading to the lowest J values were around the optimum values of s_1 and s_2, with J values increasing with the value of these parameters.

The optimal configuration of the parameters of the filter led to very satisfactory results in terms of accuracy, as shown in Fig. 3. The mean (standard deviation) RMS, *corr* and offset values for the 45 trials that were not used for the optimisation are reported in Table 2. At all observed speeds, errors were around 0.6° with average correlation coefficients greater than 0.90.

4. Discussion

This study proposed a Kalman filter for the estimation of the lower trunk movements during treadmill level walking and proved the importance of selecting proper parameters for it.

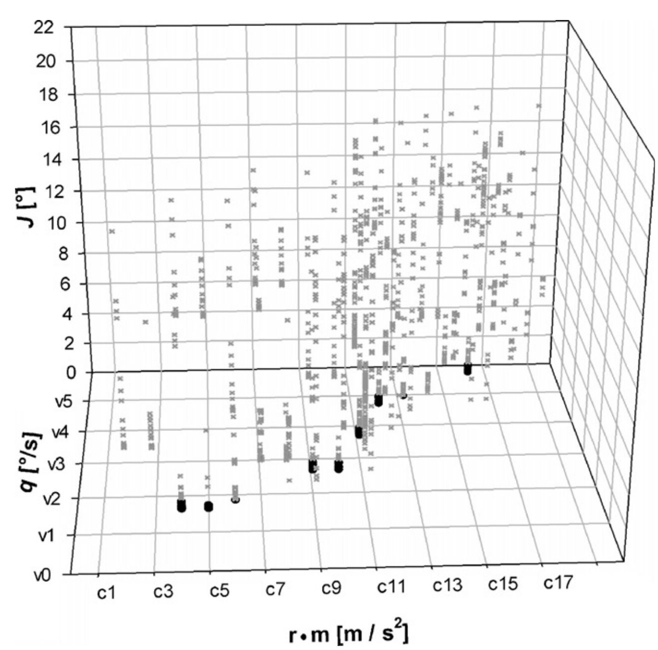

Fig. 1. The results of the sensitivity analysis. For the sake of clarity, results have only been plotted for the combinations of parameters that gave $J < 20°$, and these J values have been plotted for the combinations of the $r \cdot m$ values (c1, . . ., c17) and of the q values (v1, . . ., v5) from which they were obtained. The results relevant to the combinations of the parameters leading to values $J < 2°$ have been highlighted by plotting them in black.

As reported for other motor tasks [17], the importance of the parameters selection has been highlighted by the results of the optimization procedure and of the sensitivity analysis. It has been shown, in particular, that the three parameters q, r, and m must vary simultaneously, with the ratio $(r \cdot m)/q$ having to be constant and much greater than one. This means that for the investigated type of motor task the relative importance of the accelerometers and gyroscopes error is fixed, with the gyroscope generally being considered more reliable than the accelerometers, as already suggested by other authors [19].

Once the proper combination of q, r, and m is found, s_1 and s_2, have to be set to low values, ranging in between 0.05 and 0.2 m/s^2, in order to obtain satisfactory angle estimates. This can be explained by the fact that the observed motor task is dynamic, and its "quasi static" parts do not actually require the use of an adaptive filter, as they are typically very short and hence do not strongly influence the results of the computations. The use of an adaptive filter and the proper selection of its parameters could be crucial when different movements, involving higher deceleration and acceleration phases, are investigated [23]. We expect, for example, that this would be the case in other locomotor tasks such as running.

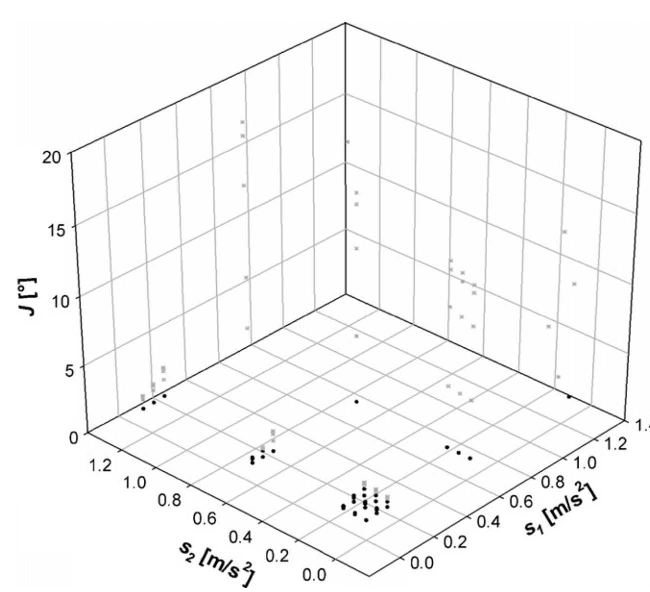

Fig. 2. The results obtained for the sensitivity analysis. The values of the index J have been reported as a function of the values of the parameters s_1 and s_2. For the sake of clarity, results have only been plotted for the combinations of parameters that gave $J < 20°$. Furthermore, the combinations of the parameters leading to values $J < 2°$ have been highlighted by plotting them in black.

Table 2
Results of the accuracy analysis.

Trial type	Filter	Pitch			Roll		
		RMS (°)	*corr*	Offset (°)	RMS (°)	*corr*	Offset (°)
Slow	No	8.1 (0.9)	−0.26 (0.16)	3.4 (0.7)	6.7 (1.3)	0.04 (0.21)	1.3 (0.5)
	Yes	0.6 (0.1)	0.91 (0.04)	3.6(1.1)	0.5 (0.1)	0.93 (0.07)	1.3 (0.6)
Natural	No	9.6 (0.7)	−0.27 (0.22)	3.4 (0.7)	7.8 (1.5)	0.01 (0.16)	1.2 (0.5)
	Yes	0.6 (0.1)	0.91 (0.03)	3.5 (0.9)	0.5 (0.1)	0.93 (0.06)	1.3 (0.7)
Fast	No	10.6 (1.3)	−0.22 (0.21)	3.1 (0.9)	10.0 (1.9)	−0.09 (0.13)	1.4 (0.7)
	Yes	0.7 (0.2)	0.91 (0.03)	3.6 (1.0)	0.6 (0.1)	0.92 (0.05)	0.9 (1.1)

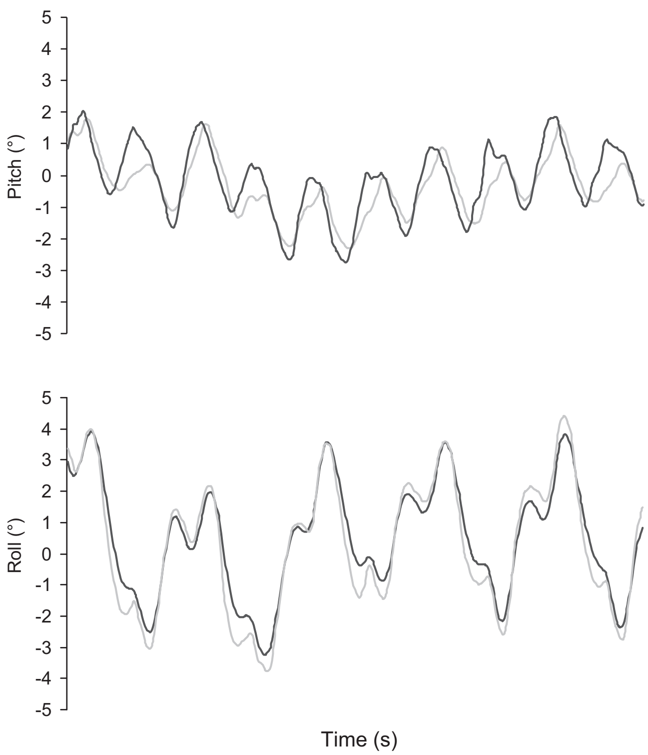

Fig. 3. Example of the estimate of the pitch and roll angles as obtained during a consecutive series of walking cycles extracted from a trial at natural speed. Angles estimated with photogrammetry (grey line) are compared to those estimated using the IMU data and the optimized Kalman Filter (black line).

Once the optimized parameters were selected, the filter proved to be very robust with respect to walking speed and subjects' anthropometry, as shown by the very low residual differences to orientation data obtained with stereophotogrammetry. Since the difference between treadmill and overground walking mainly affects self-selected walking speed and, very mildly, stride length [24], it can be hypothesised that the results of this study may be valid for the latter type of locomotion as well. However, evidence is required to confirm this hypothesis. RMS differences were lower than 1° and were close to the accuracy with which the same angles can be measured with the stereophotogrammetric system. As expected, the offsets between the curves, that were around 3.5° for the pitch and around 1.3° for the roll, were not modified by the filter and were not noticeably affected by the optimization procedures. This may also be a consequence of the fact that they were not included in the calculation of the cost function. This choice is justified by the fact that these values reflect possible misalignments of the global reference frames adopted for the two measurement systems and should hence have already been minimized during the calibration of the systems.

Whereas the importance of the selection of the correct parameters is a concept that can certainly be generalized, the specific values proposed in the study are only valid for the class of sensors used, since they depend on the electronic noise of their components, and for the investigated locomotor act, since they depend on the features of its accelerations and angular velocities. For the sake of practicality, a method not requiring the use of stereophotogrammetry as a concurrent measurement system needs to be developed for the tuning of the filter parameters. A mechanical device imposing a *priori* known rotations at predefined angular speeds which replicate those found in selected human movements could be a feasible alternative.

In conclusion, the proposed filter can be used for reliably estimating trunk lateral and frontal bending during walking for an extended period of time over a wide range of speeds. This information, if used together with other parameters, derived from an inertial sensor output located on the lower trunk (such as temporal and spatial parameters and those describing the pelvis movements) is certainly of interest for assessing walking ability. Further studies are needed to determine the filter parameters that are most suited for other motor tasks.

Conflicts of Interest

One of the authors, Marco Donati, is currently employed by the company (Sensorize srl) that produces and distributes the inertial sensor that was used for the experimental sessions described in the paper.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.gaitpost.2011.08.024.

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