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The Use of an Orientation Kalman Filter for the Static Postural Sway Analysis

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Abstract

The paper presents a quaternion-based extended Kalman filter for postural instability evaluation during stance. It uses low-cost MEMS inertial sensors attached on the lower back of the person at a known height in order to instrumenting the static balancing test. Generally, patients with Parkinson's disease or vestibular-loss are at greater risk for having this problem. The objective of this study was to assess the feasibility of using Kalman filter to characterize the postural steadiness. The Kalman filter is used here as a data fusion algorithm to estimate the orientation of the body based on acceleration and angular rate signals. In order to get the coordinate of the body's centre of mass (CoM), the height of the sensor is projected on the horizontal plane by using the estimated orientation. Many parameters such as the mean velocity of sway, lateral/anterior-posterior range and others are then obtained from the sway path, which help the clinicians to assess the postural instability. The method was tested on 9 healthy individuals (21-31 years). Three different test conditions, namely feet comfortable stance with eyes-open, feet together stance with closed eyes and one-leg stance with eyes-open were evaluated here. The proposed algorithm showed successful estimation of the time-domain parameter for the postural sway analysis.

Keywords: KALMAN FILTER, INERTIAL SENSORS, STANDING BALANCE ASSESSMENT

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1. Introduction

Postural instability is one of the common symptoms which appear in patients with neurological disorders such as Parkinson's disease and vestibular-loss. The patient is unable to maintain the fixed upright position during stance which is caused by involuntary body movements (backwards and forwards with lateral sway). Therefore a system to measure this instability is advantageous for clinical assessment, especially for rehabilitation intervention. In general, balance problems increase with age [1] and also by altered sensory, motor or central nervous function caused by Parkinson's disease or peripheral neuropathy.

Many researchers used tri-axial accelerometer-based system, attached on the center of mass, to extract the quantitative parameters for balance [2-6]. The work in [2-3] showed a method based on acceleration measurements, in which it computes the coordinates of the traced path. The approach was compared with force platform measurements and it showed that the two systems follow the same behavior between test conditions. On the other hand, the work in [4-6] computed the balance metrics directly from the acceleration trajectories in the horizontal plane. The studies were applied on the group of patients with PD. The results showed the extracted parameters from acceleration measurements which are able to distinguish between the groups.

Mellone *et al.* [6] presents a Hilbert-Huang-Based filter to remove tremor signal before the calculation of balance parameters takes place. For patients with PD one should consider the effect of tremor on the calculation of balance parameters, therefore a tremor removal filter is advantageous in this case. The frequency bandwidth of the stabilization process in quiet standing is mainly below 3 Hz while the tremor is located typically between 4 and 7 Hz.

Other researchers like [7] use the Gyroscope measurements, instead of accelerometer measurements, to distinguish between normal and deficient balance control. Originally, force platforms were used mainly in clinics for many studies to characterize the postural steadiness [8-10]. Alongside, a variety of postural measures (e.g. mean velocity, mean distance and sway area) was used to help understanding age- and disease associated sway.

Currently, the sensor fusion algorithms like Kalman filtering are still not investigated in detail for the calculation of balance parameters based on gyroscope and accelerometer measurements. Here, a Kalman filter is presented to estimate the orientation of the body. The approach uses the estimated inclination (pitch and roll angle) to project the height of the sensor unit which is known beforehand, on the horizontal plane by using the trigonometric function. Hence the coordinate of the body's CoM is computed continuously to form the trajectory of sway. In the study, the algorithm was tested on healthy individuals for different test conditions.

The rest of the paper is structured as follows: Section 2 provides information about the test subjects with the measurement unit. The section describes the measured balance parameters and the Kalman filtering with the proposed method to calculate the sway trajectory. Section 3 shows the experimental results with the discussion. Finally, the conclusions and future work are presented in section 4.

2. Materials and methods

2.1. Subjects and procedure

Nine healthy persons (age range: 21-31 with average 25.6, gender: 9 male) without specific diseases of the nervous, vestibular, or muscular systems or balance disorders were asked to perform the static balance test. The participants were asked to perform the test for three trails in short succession, in which they took a rest on a chair before performing the next trail. For each trail, three condition tests were done: standing with feet in comfortable position and open eyes (EO-CP), standing with feet together and closed eyes (EC-TP) and one-leg standing with eyes open (EO-OL). In all test conditions and trails, the test was performed on normal surface. During the test, the person was standing in upright position.

For the test, the inertial unit was placed on the lower back of the person at the approximate height of the body's CoM by using a double sided adhesive tape and an elastic band to ensure fixed attachment (Fig. 1). The duration of each trail took 1 minute in which only 40 seconds used for evaluation to let the filter converge in the initial time.

Fig. 1. Posterior view of the placement of the inertial measurement unit (IMU), the unit was placed on the lower back by using a double sided adhesive tape with a band. The figure shows as well the inertial unit fixed on the band

2.2. The sensor unit

The participants wore an IMU on their lower back in the area between the L3 and L5 vertebrae. The unit includes a 3-axis accelerometer (range: ±4g, resolution: ±0.004 g/digit) and a 3-axis Gyroscope (range: ±500 deg/s, resolution: ±0.07 deg/s/digit). In the study, the acceleration and angular rate were measured synchronously at a sampling rate of 400 Hz and the measurement have been sent to a host PC via a USB interface to log the inertial data (Fig. 2). The data were filtered at a cut-off frequency of 4 Hz by a low-pass 4th order FIR filter with zero-phases. The filter is used to remove the noise and tremor signals.

Fig. 2. The IMU which was used for the test

2.3. Balance quantitative parameters

Eight postural parameters have been proposed in this study to describe the planar (2D) of CoM [8-9]. For the equations listed below, let N be the number of sampling point and T represents the time for the test execution. In the dataset, each point is represented by (x_i, y_i) . For each measured parameter, the corresponding axes namely: Anterior-Posterior (A/P) and Medial/Lateral (M/L) can be similarly calculated. First the mean of each signal is removed from the time series of each CoM then the following parameters were measured:

- Sway Area (SA):

It is the area enclosed by the CoM path per unit of time. It is approximated by accumulating the triangles area, which is formed by two consecutive points on the sway trajectory and the mean CoM, divided by the total time.

- Mean Distance (MD):

It is the mean distance between the points of the sway trajectory and the mean of CoM. It is approximated by summing the distance of each pair of points to the mean CoM and then divided by the number of samples.

$$MD = \frac{1}{N}\sum_{i=1}^{N}\sqrt{x_i^2 + y_i^2} \tag{1}$$

- Mean Velocity (MV):

It is the division of the total length of the sway path (SP) by the travelled time. The total length is calculated by summing the distance between each consecutive pair of points.

$$SP = \sum_{i=1}^{N-1}\sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \tag{2}$$

$$MV = SP/T \tag{3}$$

- Mean Frequency (MF):

It is the number of revolutions per one second which is taken in a uniform circular motion with a radius of MD and a total length of sway trajectory of ST.

$$MF = \frac{SP}{2\pi MD}\frac{1}{T} \tag{4}$$

- Range (R):
  It is the absolute difference between the highest and lowest value in the data set.

- Root-Mean-Square Distance (RMS-D):
  It is the square root of the mean of the squares of the data. The parameter represents the standard distribution of the data.

$$MT = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i^2 + y_i^2\right)} \tag{5}$$

2.4. Error-state Kalman filter

The Kalman filter is a recursive data fusion algorithm which estimates the state of a dynamic system from noisy measurements. The state-space equations in the indirect (error-state) Kalman filter are formed by expressing the change of errors with respect to time. The filter estimates the difference between the true x and the estimated $\hat{x}$ state:

$$\hat{x} = x + \delta x \tag{6}$$

For the continuous linear system, the state-space model is expressed as follows [11]:

$$\delta\dot{\vec{x}} = \Phi(t)\delta\vec{x} + G(t)\vec{w} \tag{7}$$

where Φ represents the state transition matrix, G is the mapping matrix into state vector and $\vec{w}$ is a zero-mean white Gaussian noise. On the other hand, the measurement equation is given in discrete time by:

$$\delta\vec{z}_k = H\delta\vec{x}_k + \vec{v}_k \tag{8}$$

where $\delta\vec{z}$ is the difference between the predicted and real measurement. H matrix represents the Jacobian of the measurement function. The random variables represent the process and measurement noises respectively. They are white noise with normal probability distribution $\vec{w} \sim \aleph(0, Q)$ and $\vec{v} \sim \aleph(0, R)$.

2.5. Filter design

Here an error-state Extended Kalman filter is used for the orientation estimation. The filter tracks the orientation using quaternion to avoid the problem associated with Euler angle singularity [13] and also for its efficiency in computation [14]. Here, the unit quaternion is used to describe a rotation of angle θ about unit axis $\vec{\mu}$ as follow:

$$q = \begin{bmatrix} q_w & \vec{q} \end{bmatrix}^{\mathrm{T}} = \begin{bmatrix} \cos(\theta/2) & \sin(\theta/2)\vec{\mu} \end{bmatrix}^{\mathrm{T}} \tag{9}$$

where q_w represents the scalar part of the quaternion and $\vec{q}$ is the corresponding vector part. The attitude dynamic of the rigid body is expressed in term of unit quaternion by

$$\dot{q} = \Omega(\omega)q \tag{10}$$

where $\Omega(\omega)$ is the skew-matrix on the angular rate. The error state vector $\begin{bmatrix} \delta\vec{q} & \delta\vec{b}_\omega \end{bmatrix}$ is composed of the vector part of the error quaternion and the three-axial Gyroscope biases error vector. The three element vector part of quaternion error vector is used instead of the four-element error vector to avoid covariance matrix singularity [12]. The continuous time state transition vector equation is written in the form:

$$\begin{bmatrix} \delta\dot{\vec{q}} \\ \delta\dot{\vec{b}}_\omega \end{bmatrix} = \begin{bmatrix} \lfloor\tilde{\omega}\times\rfloor & 0_{3\times3} \\ 0_{3\times3} & 0_{3\times3} \end{bmatrix} \begin{bmatrix} \delta\vec{q} \\ \delta\vec{b}_\omega \end{bmatrix} + \begin{bmatrix} -1/2\,\mathrm{I}_{3\times3} & 0_{3\times3} \\ 0_{3\times3} & \mathrm{I}_{3\times3} \end{bmatrix} \begin{bmatrix} \vec{w}_\omega \\ \vec{w}_{b_\omega} \end{bmatrix} \tag{11}$$

where $\lfloor\tilde{\omega}\times\rfloor$ is the skew-symmetric matrix of the measured angular velocity which is used as an operator for the cross-product, $\vec{w}_\omega \sim \aleph(0, Q_\omega)$ is the zero-mean white noise of the control input and $\vec{w}_{b_\omega} \sim \aleph(0, Q_{b_\omega})$ is the process zero-mean white noise of the gyroscope bias. The gyroscope bias is modeled as a random walk.

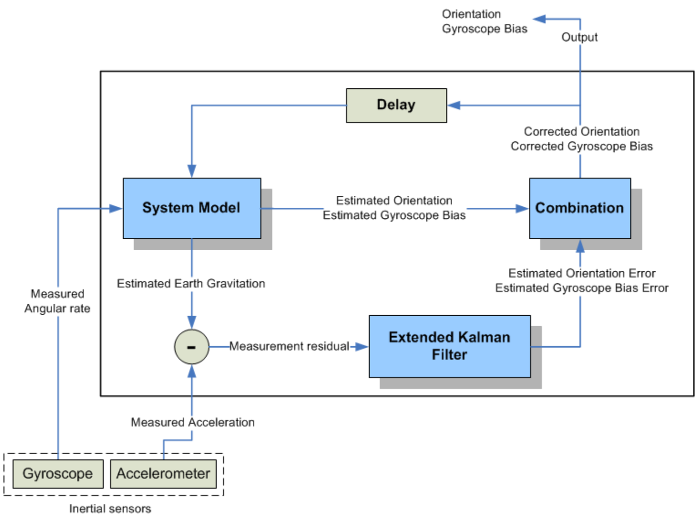

Fig. 3. Schematic diagram of the error state orientation filter

The discrete version of the process model (11) is used for the EKF formulation. The measurement model relates the measurement error to the state vector and is given in discrete form as:

$$\delta\vec{z}_{k+1} = \delta\vec{a}_{k+1} = -2\lfloor\hat{a}_{k+1}\times\rfloor\delta\vec{q} + \vec{v}_{k+1} \tag{12}$$

where $\lfloor\hat{a}_{k+1}\times\rfloor$ is the skew-symmetric matrix of the predicted measurement for acceleration $\hat{a}$ and $\vec{v}_{k+1} \sim \aleph(0, Q_a)$ is the measurement zero-mean white noise of the acceleration. The predicted acceleration measurement can be calculated by

$$\hat{a}_{k+1} = C_n^b\left(\hat{q}_{k+1}^-\right)\vec{g} \tag{13}$$

with $\vec{g} \approx [0 \quad 0 \quad 9.81]^{\mathrm{T}}$ m/s^2 and $C_n^b\left(\hat{q}_{k+1}^-\right)$ represents the rotation matrix that transforms a vector from navigation to body frame. From the estimated orientation, the coordinate of the body's center of mass (CoM) can be obtained by projecting the height of the sensor $\vec{h}$ on the horizontal plane (Fig. 4). The projection is done with help of quaternion:

$$\vec{s}_{k+1} = C_n^b\left(\hat{q}_{k+1}^+\right)\vec{h} \tag{14}$$

where $\bar{s}_{k+1}$ is the projected height on the horizontal plane and the two consecutive points namely (x_i, y_i) and (x_{i+1}, y_{i+1}) form a segment from the sway path.

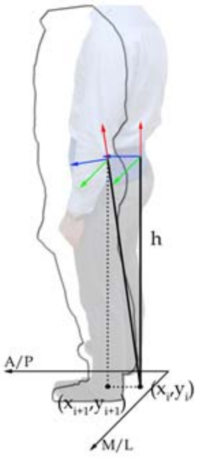

Fig. 4. The tracing of the body's CoM by projecting the sensor's height $\vec{h}$ on the horizontal plane. The point (x_i, y_i) represents the projection in iteration i while (x_{i+1}, y_{i+1}) is the next projection

3. Results and discussion

All data processing and statistical evaluations were performed with MATLAB (version 7.10). For each test condition, three trails were conducted by each individual. Therefore a set of 81 measurements in total was used to evaluate the algorithm.

Figure 5 shows an example of the sway trajectory which is calculated by using the proposed method. The results belong to the same individual from the test group and for three test conditions. It can be seen in the figure that the sway areas are well identified for all test conditions, additionally it can be observed that the sway area increases proportionally with increasing the difficulty to maintain the postural balance. In the example, the EO-CP condition has the smallest area (area = 53.04 mm^2) while the EC-TP test allocates larger area (area = 321.18 mm^2) than the EO-CP but lesser than the EO-OL condition (area = 613.12 mm^2). The total area was estimated by using the convex hull method.

On the other hand, Table 1 shows the measured parameters, listed in section 2.3, represented in their means and standard deviations. The parameters were measured from the displacement time series, i.e. the Euclidean distance between each sample point and the centered CoM, and also from A/P and M/L time series. In the study the measurement from a force platform was not present due to their unavailability, therefore the three test conditions, namely EO-CP, EC-TP and EO-OL were selected to reflect the tendency of increasing in the difficulty to perform a stable stance. The EO-CP condition is considered as the easiest case, while EO-TP is expected to be in the middle state as the sway increases when eyes are closed. EO-OL condition, when one leg standing is performed should show highest sway. The former statement is confirmed as well by the results in Table 1 which show an increased tendency in the measured parameters (mean distance, rms distance, sway area, mean velocity, range and total power).

For all the test conditions, the mean frequency parameter did not show comparable results between the conditions. The reason for this is that the data were drawn from healthy individuals therefore the number of uniform circular motion produced per one second is kept relatively in the same value when these test conditions were performed on healthy individuals.

Here the Wilcoxon rank sum test was used to compare the difference between the groups [15]. The Wilcoxon rank sum test is a nonparametric statistical test which is used to test the null hypothesis of two independent samples drawn from the same population. The test determines if the means of their population are significantly different. Table 2 shows the p-values which compares all test conditions. All parameters in the table show statistically clear significant differences between the three conditions ($p < 0.05$).

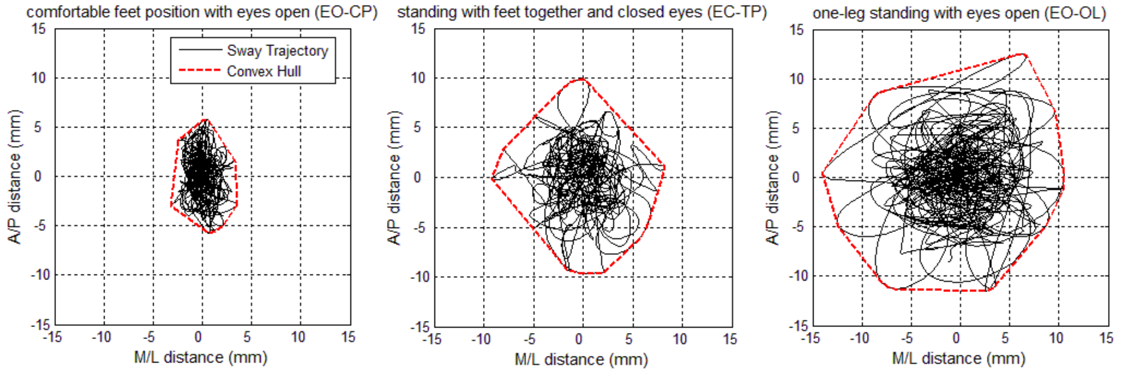

Fig. 5. Example of sway trajectory of the three test conditions which belongs to one of the participant in the test. The outline of the sway area is determined by the convex hull. The estimated area by convex hull is 53.04 mm^2 for EO-CP, 321.18 mm^2 for EC-TP and 613.12 mm^2 for EO-OL. Left figure: sway path for the postural test of comfortable position with open eyes (EO-CP), middle figure: standing with feet together with closed eyes (EC-TP), right figure: one-leg standing with opened eyes (EO-OL)

Table 1. Mean values and standard deviation of the quantitative parameters for the three test conditions

	EO-CP		EC-TP		EO-OL	
	mean	std	mean	std	mean	std
Mean distance (mm)	2.86	0.62	5.13	0.88	6.46	1.26
Mean distance A/P (mm)	2.42	0.62	3.61	0.62	4.33	0.95
Mean distance M/L (mm)	1.07	0.17	2.93	0.74	3.89	0.79
RMS distance (mm)	3.35	0.77	5.92	1.04	7.47	1.48
RMS distance A/P (mm)	3.04	0.77	4.55	0.83	5.52	1.22
RMS distance M/L (mm)	1.38	0.25	3.74	0.90	4.99	1.03
Sway area (mm^2/s)	22.83	7.32	54.95	19.04	156.45	65.42
Total sway area (mm^2)	128.34	59.69	432.85	160.79	881.21	382.92
Mean Velocity (mm/s)	25.16	3.53	32.93	5.57	6910	14.90
Mean Velocity A/P (mm/s)	16.65	1.89	21.12	4.88	38.39	9.50
Mean Velocity M/L (mm/s)	15.30	3.01	20.72	2.94	49.20	11.39
Range (mm)	18.37	5.20	30.02	6.39	39.76	9.56
Range A/P (mm)	18.20	5.20	28.19	7.19	34.30	7.94
Range M/L (mm)	10.03	2.96	22.35	4.36	34.57	9.79
Mean frequency (Hz)	1.44	0.24	1.03	0.14	1.71	0.25
Mean frequency A/P (Hz)	1.14	0.23	0.94	0.13	1.43	0.27
Mean frequency M/L (Hz)	2.27	0.17	1.14	0.17	2.02	0.26

Table 2. The p- values of rank sum test between the three conditions. (* < 0.0001)

	Rank sum p-values		
	EO-CP vs. EC-TP	EO-CP vs. EO-OL	EC-TP vs. EO-OL
Mean distance	0.0000*	0.0000*	0.0002
Mean distance A/P	0.0000*	0.0000*	0.0033
Mean distance M/L	0.0000*	0.0000*	0.0001
RMS distance	0.0000*	0.0000*	0.0002
RMS distance A/P	0.0000*	0.0000*	0.0034
RMS distance M/L	0.0000*	0.0000*	0.0001
Sway area	0.0000*	0.0000*	0.0000*
Total sway area	0.0000*	0.0000*	0.0000*
Mean velocity	0.0000*	0.0000*	0.0000*
Mean velocity A/P	0.0000*	0.0000*	0.0000*
Mean velocity M/L	0.0000*	0.0000*	0.0000*
Range	0.0000*	0.0000*	0.0001
Range A/P	0.0000*	0.0000*	0.0077
Range M/L	0.0000*	0.0000*	0.0000*
Mean frequency	0.0000*	0.0007	0.0000*
Mean frequency A/P	0.0009	0.0002	0.0000*
Mean frequency M/L	0.0000*	0.0005	0.0000*

A Similar approach to calculate the sway path is to use the accelerometer measurements alone [2-3]. However it is known that using a Kalman filter has advantages compared to this method [16]. The estimation of inclination based on acceleration measurements is obtained basically by measuring gravitational vector; therefore the estimation can be easily perturbed by measuring other acceleration components like centrifugal or Euler accelerations. Another advantage of a Kalman filter is the fusion of sensor data, for example here the fuse of gyroscope measurements which tracks high dynamic motion and therefore can support the better estimation of inclination. On the other hand, a clear disadvantage of the Kalman filter is the demand for more time complexity.

The initial results presented above in this study based on healthy group and their significant difference between the conditions confirms the principle relevance for clinical use of this algorithm. The conclusions need certainly further evaluation with data from patients.

4. Conclusions

We have proposed an orientation Kalman filter for the clinical standing balance assessment. The method uses both gyroscope and accelerometer measurements on the lower back. The filter combines accelerometer and gyroscope measurements to obtain a robust inclination against sensor disturbance and linear acceleration when it is compared with the individual sensor. The fusion corrects the drift of the gyroscope and attenuates the influence of acceleration such as centrifugal or Euler acceleration. Moreover, the proposed method is independent of the sensor unit attachment on the body.

The low-cost of the system and its usability at the home-environment with relatively small size reveals the importance of such a system design for clinical assessment. In future work, it is planned to validate the algorithm with a force platform and the system will be as well tested with data from patients of Parkinson’s disease.

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