Al-Jawad A., Romanovas M., Klingbeil L., Traechtler M., Mergner T., Fennell L., Manoli Y. (2011)
A System for orientation and acceleration estimation in an artificial vestibular system.
Mikrosystemtechnik-Kongress 2011, Oct. 10-12, Darmstadt, Germany.

A System for Orientation and Acceleration Estimation in an Artificial Vestibular System

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Abstract

We present an error-state formulation of a Kalman filter used for an artificial self-contained vestibular system. The Kalman filter is used in this work as a data fusion algorithm where the acceleration and angular rates signals are combined in order to obtain the correct estimation of the applied linear acceleration and the inclination angle. The paper compares a biologically inspired approach expressed as a complementary filter (CF) to a merely engineering approach for the fusion problem. The latter is expressed in a form of an Extended Kalman filter (EKF) and both methods are based on signals from low-cost MEMS sensors. Each of the presented schemes acts as an artificial vestibular sensor and can be employed as a part of the higher level systems such as the stance control.

1 Introduction

The vestibular system contributes to human spatially oriented functions such as balancing of a biped stance, where it fuses signals from two transducer organs: the otolith and the canal systems for obtaining a reliable measure (see [1] for a recent overview). The otolith system provides a measure combining both head orientation with respect to the gravity vector and inertial forces due to translational head accelerations. The canal system provides a signal of head angular velocity, in which a low frequency noise is largely, but not completely reduced by a high pass filtering defined by a canal time constant. The fusion yields a gravito-inertial force resolution and improves the quality of the canal signal.

Due to the recent progress in MEMS inertial sensors one could intend to employ them for construction of an artificial self-contained vestibular system for the human stance stability. Here the signals from acceleration and angular rate sensors are merged using advanced Sensor Data Fusion (SDF) techniques. Although numerous works have investigated the design and implementation of orientation estimation systems using low-cost MEMS inertial sensors (see [2, 3] for references), these systems were mainly designed for non-medical applications such as object tracking or Attitude Heading Reference Systems (AHRS). Rather few attempts [1] so far have been aiming at neurological applications with requirements typical for those in human functions such as stance control. Our research goal is to develop and investigate an artificial vestibular system for use in a multi-modal sensor integration bearing in mind the requirements for disturbance rejection, motion dynamics, and signal characteristics within the human balancing system [1].

The system will be combined with other sensors such as force and joint angle sensors (see Fig. 1) for complementary information similarly as it is done within a real human postural control system. The work compares the biological approach originally developed in to an engineering technique reformulated as an estimation problem using error-state Kalman filtering framework. The biologically inspired method is a complementary filter (CF) where the fusion performed at the stage of angular rates rather than the angles. The alternative in the form of EKF is an engineering approach typically employed for nonlinear estimation tasks such as orientation estimation from noisy sensor measurements.

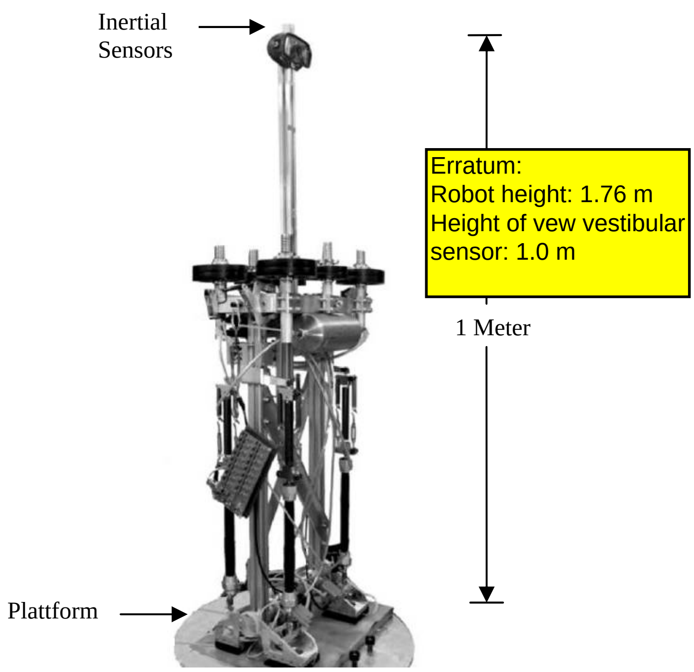

Figure 1 The Robotic setup for human stance control which is developed in a neurological laboratory of Freiburg University.

The paper is outlined to start with the discussion on the hardware and the formulation of the associated estimation algorithms. Then the corresponding experimental results of both biological and engineering approach are presented and the relevant conclusions are drawn at the end of the paper.

2 Hardware/Sensors

The developed platform (see Fig.2) comprises a 3-axis MEMS accelerometer and 3-axis MEMS angular rate sensor (both sensors are within the same module Analog Devices ADIS16364) connected to an MCU via SPI for a real-time data acquisition. Scaled and pre-processed sensor data are further transferred via serial interface to a special computational unit (mbed NXP LPC2368 platform [4]) for online data fusion.

As an alternative solution to ADIS-based system, a miniaturized sensor unit (see Fig.3) has been developed consisting from low-cost consumer discrete sensor elements (STM LIS3LV02DL 3-axis digital accelerometer and InvenSense ITG-3200 3-axis digital gyroscope). A microcontroller (TI MSP430) is added for data acquisition and retransmission. In contrast to Analog Devices sensor unit, a calibration procedure for sensors in a final setup has to be carried out by the user and was performed using a reference 3-axial rate table from Acutronic located in HSG-IMIT facilities.

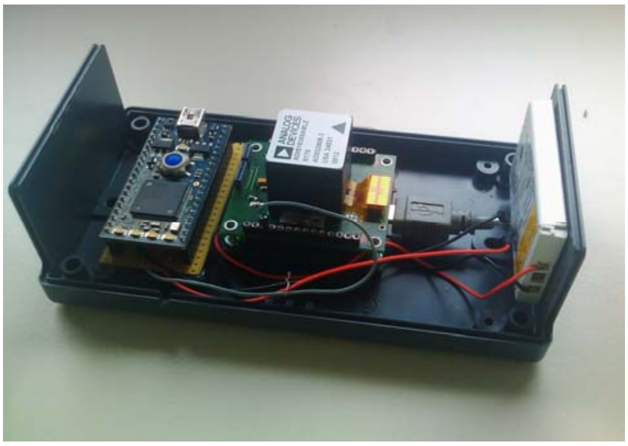

Figure 2 The development platform with inertial sensors (ADIS) and mbed processing unit.

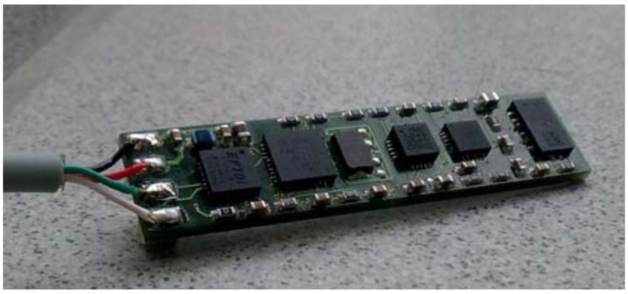

Figure 3 The miniaturized platform with inertial sensors.

During the experiment, both systems were sampled at a rate of 100Hz and the measurements have been sent to a host PC via a USB interface to log the inertial data. Both systems were designed to be powered by the USB connection. The assessment of both filters is taken place at the computer using Matlab.

3 Kalman Filtering

The Kalman filter is a recursive data fusion algorithm that estimates the state of a dynamic system from a series of noisy measurements. The total information regarding the estimate is represented by 2 terms: the estimate mean vector and the associated covariance matrix, describing the uncertainty bounds of the estimates. Each filter cycle consists of 2 sequential stages: the prediction step based on a known or assumed process model for the state and covariance propagation in time with respect to control inputs and process noise assumptions, and the associated correction step, where the noisy prediction measurements are employed to update the predicted filter's state via its known relationship to existing observations in the form of measurement model and associated sensor noises. In this work the merge of the different sources of information is achieved by an error-state Extended Kalman filter, where the errors of the state variables instead of the variables themselves are included into the filter's state. Here the error-state formulation is chosen for more robustness [5]. Then the filter estimates the difference between the true state and the estimated one:

$$\delta x = x - \hat{x}\,. \tag{1}$$

The method from above will be compared to a biologically motivated CF, where the outputs of the accelerometers and gyroscopes are combined in the filter at the level of angular velocity signals with different noise properties (Fig. 4) to compensate for the drift of the rate gyro and for the slow dynamics of the accelerometer The complete biological model of canal-otolith fusion is shown in Fig. 5. It consists in addition to the complementary filter the estimation of attitude $\hat{g}$ and translational acceleration $\hat{a}_i$ (for detailed description see [1]).

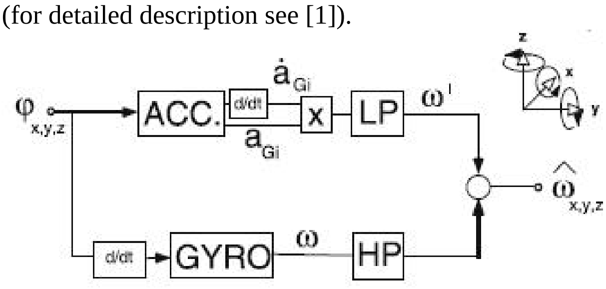

Figure 4 Canal-otolith signal fusion based on CF [1].

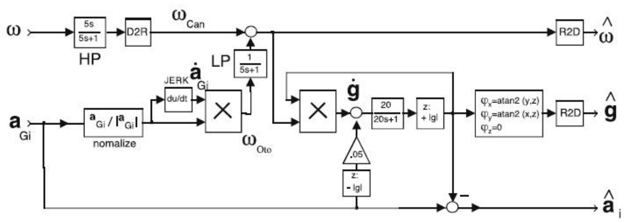

Figure 5 Canal-otolith fusion model [1].

These two solutions: the engineering and biological approaches, estimate angular velocity, translational acceleration and attitude (pitch and roll as heading is essentially non observable) which correspond to the outputs of the vestibular system and can be used in a stance control.

Orientation Estimation

The Kalman filter has been widely used for orientation in which it serves as a sensor fusion algorithm. In this work, it is formulated in the error-state form [5, 7], where both 3D orientation and translational acceleration are estimated (see Fig. 6). The bias of the MEMS gyroscopes is eliminated using a high-pass filter in the pre-processing stage of the EKF. A quaternion-based attitude representation is chosen, due to its computational efficiency and the absence of singularity problems [2]. It is represented by

$$q = \begin{bmatrix} q_w & q_x & q_y & q_z \end{bmatrix}^{\mathrm{T}} = \begin{bmatrix} q_w & \bar{q} \end{bmatrix}^{\mathrm{T}} \qquad (2)$$

The vector part of the quaternion is given by $\bar{q}$ while q_w represents the scalar part. The error state $\begin{bmatrix} \delta\bar{q} & \delta\vec{\rho} \end{bmatrix}^{\mathrm{T}}$ of the Kalman filter contains six components, namely the vector part of quaternion $\delta\bar{q}$ to represents 3-Degree Of Freedom (3-DOF) orientation and the translational acceleration $\delta\vec{\rho}$. The three element vector part of quaternion error vector is used instead of the four-element error vector to avoid covariance matrix singularity [7].
In the process model, the quaternion attitude kinematics [8] is used as a model in the filter and the translational acceleration is modelled to decay exponentially with time constant τ. Here the gyroscope measurement is treated as an input control for the process model in the filter. The continuous time state transition equation is written in the form:

$$\begin{bmatrix} \dot{\delta\bar{q}} \\ \delta\vec{\rho} \end{bmatrix} = \begin{bmatrix} \lfloor \tilde{\omega} \times \rfloor & 0_{3x3} \\ 0_{3x3} & -\frac{1}{\tau} \mathrm{I}_{3x3} \end{bmatrix} \begin{bmatrix} \delta\bar{q} \\ \delta\vec{\rho} \end{bmatrix} + \begin{bmatrix} -\frac{1}{2} \mathrm{I}_{3x3} & 0_{3x3} \\ 0_{3x3} & \mathrm{I}_{3x3} \end{bmatrix} \begin{bmatrix} \vec{w}_g \\ \vec{w}_\rho \end{bmatrix} \qquad (3)$$

where $\lfloor \tilde{\omega} \times \rfloor$ is the skew-symmetric matrix of the angular rate which is used as an operator for the cross-product, $\vec{w}_g$ is the control input noise and $\vec{w}_\rho$ is the process noise of the translational acceleration.
The discrete version of the process model (3) is used for EKF formulation. The measurement model relates the acceleration measurement error $\delta\vec{a}_{k+1}$ to the state vector and it is given by

$$\delta\vec{z}_{k+1} = \delta\vec{a}_{k+1} = -2\lfloor \hat{a}_{k+1} \times \rfloor \delta\bar{q} + \delta\vec{\rho} + \vec{v}_{k+1} \qquad (4)$$

where $\lfloor \hat{a}_{k+1} \times \rfloor$ is the skew-symmetric matrix of the predicted measurement for acceleration ($\hat{a}$) and $\vec{v}_{k+1}$ is the measurement noise.

Because the accelerometer measures physical quantities, such as linear and centripetal accelerations, along with the earth gravity, the algorithm is developed for decoupling the Earth's gravity component from linear and centripetal accelerations, measured by the accelerometers.
The orientation algorithm (Fig. 6) contains a system model block and an EKF block. In the system model, the next orientation in each filter's iteration is predicted by means of the filtered gyroscope's angular velocity. This orientation is used to estimate the earth gravity in the body frame, which is subtracted from the measured values to compute the measurement residual. The estimated error state is used to correct the predicted state that is computed previously in the system model [6].

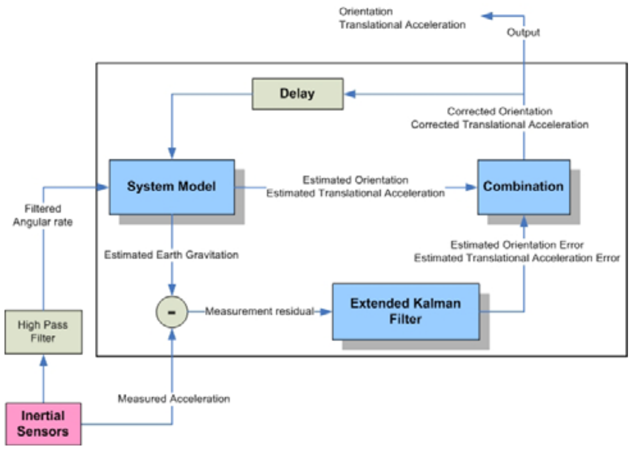

Figure 6 Schematic diagram of the error state orientation filter.

4 Experiment

The performance of both fusion filters was evaluated using a number of experimentally obtained data sets from a humanoid robot (see Fig. 1) built by the neurological group of Freiburg University in order to mimic the main features of human posture. The setup consists of a platform where the humanoid robot stands on. The artificial vestibular system is mounted at the top of the robot 1 meter above the centre of the platform. A rotational motion with maximum amplitude of ±4 degrees and as well translational motion with maximum displacement amplitude of ±1.75 cm is applied on the platform over a frequency range of 0.05-0.8 Hz. The motion of the platform itself has been also recorded and constitutes the reference dataset for the evaluation of filter performances.
Eight datasets (three pure rotational motions, three translational motions and two sets of combined rotational and translational motions) with different frequencies were collected during our study. In the discussion below we present the results for combined dataset as it includes both simultaneous rotation and translational motions.

Test Results

The filters were evaluated using Matlab and recorded sensor data and the estimation results have been compared to the reference data from the robotic platform. In Fig. 7 the estimate of the filters are shown together with the reference tilt angle and the translational acceleration. We clearly see that both the EKF and the CF are able to track the true robot orientation. The introduced fixed offset in the estimation of filters is due to a mismatch of the sensor setup when placed at the top of robotic platform. Fig. 8 shows the error of filters with the reference data.

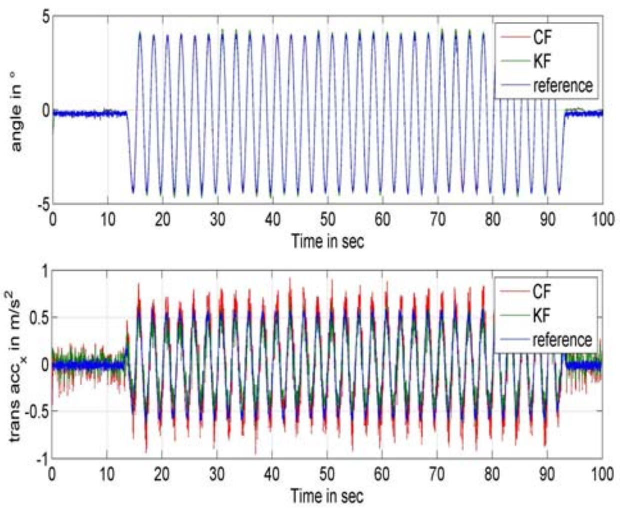

Figure 7 Dataset of combined rotation stimuli (sine wave with amplitude of ±4 degree and frequency of 0.4 Hz) and translational acceleration along x axis with the maximum displacement of ±1.75 cm and frequency of 0.4 Hz. Blue line represents the reference data from the controlled robotic platform where the green and red lines correspondingly the estimation results EKF and CF.

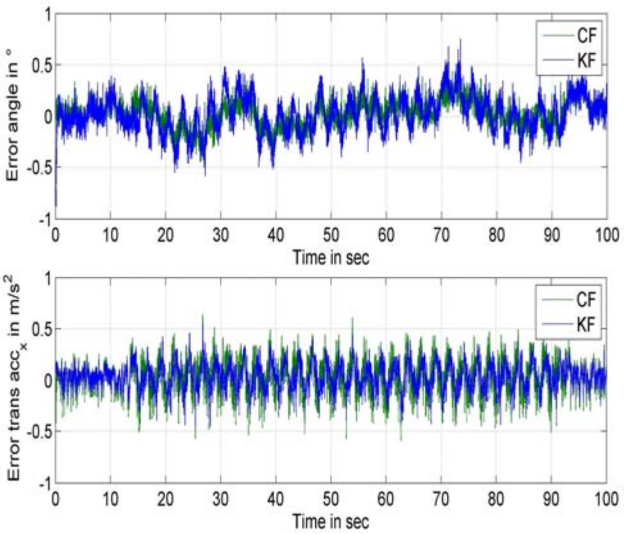

Figure 8 Error of the angle and the translational acceleration between Kalman filter and reference (blue line) and between Complementary filter and reference (green line).

5 Conclusions

The paper presents a reformulation of the artificial vestibular system in the form of an Extended Kalman filter and corresponding realization using low-cost MEMS inertial sensors. The proposed scheme is compared to a recently proposed biologically inspired approach based on Complementary filtering. Both algorithms show very similar results in terms of estimation accuracy, but the complementary formulation is preferred for embedded implementation due to its light processing demand compared to a more general EKF. However, the complementary formulation seems to be less general compared to KF and can lead to potential difficulties when tuning for varying process models or changing measurement conditions. Moreover, incorporation of additional variables of interest or measurement modalities seems to be less straightforward compared to KF-based schemes. In future we plan to integrate the presented algorithms into the complete human balancing system using additional sensors such as pressure and joint angle.

6 Acknowledgement

The author would like to acknowledge gratefully the help and contribution of the neurological group of Freiburg University. This project is funded by the German Federal Ministry of Education and Research (BMBF) under the grand number 16SV5046.

7 Literature

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