Extended Kalman filter to detect Human body movements through inertial and magnetic sensors - Medical Applications

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Abstract

Inertial orientation tracking is something that is being looked into right now, especially when it comes to capturing human movement outside in real time. Quaternions are used to show how the navigation frame and the body frame are connected in a way that makes them rotate together. In this article, we explain how to use a quaternion-based Extended Kalman Filter to figure out how a rigid body is oriented in three dimensions (EKF). The EKF uses the readings from an Inertial Measurement Unit (IMU), which is a combination of a tri-axial magnetic sensor and an accelerometer. The solution that has been suggested is a universal filter that doesn't set the amount of freedom at the connections among the different parts of the model. Even when the observatory conditions are important, the algorithm's performance can be measured with computer simulations and real-world testing.

Keywords : Extended Kalman filter, inertia, magnetic sensing, orientation

1. Introduction

Inertial motion capture systems are made up of networks of body sensors. Here, inertial measurement unit (IMU) sensors are connected to every important part that needs to be watched (Kulbacki et al. 2015; Roetenberg et al. 2009). The tracked object model, also called the skeleton, is made up of rigid-body segments, or "bones," that are connected by joints. The motion of the person may be captured by mapping the orientations of the IMUs to certain parts of the body model. It is possible to follow the overall stance if one has information about the orientations of all of the segments throughout time. Published research shows that there are many different ways to figure out where something is based on a single IMU output signal. Some examples of these approaches are Kalman filters (Sabatini 2011; Madgwick et al. 2011) and complementing filters (Mahony et al. 2008). This strategy involves just a loose coupling and treats each component in isolation, has a number of limitations. It is not possible to readily include joint limitations into the tracking, like those that are inherent in the human anatomy. During the process of estimating, the links among the different segments are lost (Miezal et al. 2013). Additionally, it has been shown that closely linked systems, in which all parameters and measurements are evaluated concurrently in a single estimate problem, yield superior performance (Young 2010).

Young et al(2010) .'s study used the "propagation of linear accelerations across the segment hierarchy" to make it easier to find the gravity components during high-speed movements. According to Szczsna et al. (2016), the foundation of this method is a relatively simple complementary filter. The Denavit–Hartenberg convention serves as the foundation for these kinds of solutions, while Euler angles serve as the representation of orientation for them.

Extended Kalman filters are proposed by the authors of the lajpah et al. (2014) study for each segment, and they use state vectors with 18 elements. The orientation is represented by quaternions with the help of this method. Walking is the sole activity that can provide the remedy. Vikas and Crane (2016) offer an alternative idea in which the joint angle is estimated by putting more than one sensor on the segment. Measurements of vestibular dynamic inclination serve as the foundation for this system, which can only provide estimations for two Euler angles. IMU sensors allow multibody systems to estimate and monitor a variety of additional characteristics, including locations, velocities, and accelerations (Torres-Moreno et al. 2016). Lajpah et al. (2014) report errors, but they can't be compared because the experiments were done in different ways and focused on different movements. Also, the errors were calculated in a way that was not consistent. Even with these things, the average angle errors were all between 4° and 7°. The numbers that were used as references came from a variety of sources, including simulations, mechanical and optical systems, and calculations made using depth camera data.

In this article, a quaternion-based Kalman filter for AHRS is defined using an Adaptive-Step Gradient Descent (ASGD) method. In order to prevent singularities, quaternions are used in the representation of the quadrotor's orientation. In the middle of the quadrotor frame are the inertial and magnetic sensors that are used to measure angular velocity etc., After the gradient descent method and preprocessing of the accelerometer have created the observation quaternions, they are fed into the Kalman filter . The angular velocity and the observation quaternions that are generated by ASGD are brought together by the Kalman filter. Since magnetic distortion would have an effect on the calculation of level attitude (pitch and roll angles), an AHRS method was developed to isolate the magnetometer from the ASGD in order to just give heading reference. This approach is known as the AHRS algorithm. A flight controller that is compact in size has been developed for the purpose of building a quadrotor.

2. Related Works

The technique for designing a quadrotor places a significant emphasis on orientation estimation, which is also a fundamental component of real-time monitoring of human body movements (Liem M.C., 2014) and placing industrial robot arms (KluzR.,. 2014). Image-based systems (Vianchada C., 2014), magnetic tracking systems (Song Shuang, et al. 2014), and ultrasonic tracking systems have each contributed to the development of a number of algorithms for the estimate of orientation and/or location (Kim SeongJin, 2013). These techniques of origin are vulnerable to the noise of the surrounding environment and have a restricted measuring range. In recent years, inertial and magnetic sensors have been utilized more often in quadrotors or aerial robots for the purpose of orientation estimation. These sensors do not experience any restrictions in terms of their measuring range. These little modules, which can be mounted to a quadrotor and used to autonomously identify direction without the need for supplied technology, are very portable.

Because quaternions work in R4, it is much simpler to describe any rotations in R3 without encountering the singularity issue. This has led to the quaternion being a preferred alternative to the Euler angles in the process of orientation representation (Alaimo A., 2013). A strap-down inertial system typically consists of a small-size tri-axis MEMS gyroscope and accelerometer that are attached to a quadrotor. Accelerometers, on the other hand, are unable to determine orientation since they cannot detect rotation around the vertical axis. It is termed the Attitude Heading Reference System (AHRS) when it is used in a navigation system (Collinson R. P. G..2011). In his 2011 paper, Liang Yan-de discussed a Complementary Filter (CF) that makes use of magnetic and inertial sensors. The quaternion-based adaptive-gain complementary filter is a proposal that was made by Calusdian et al. (2011). Gradient Descent (GD) algorithm is an iterative approach that was reported in (Zhang Hao, 2013) and (Madgwick Sebastian O. H., 2011) utilising MARG (Magnetic, Angular Rate, and Gravity) sensors. Both of these studies were conducted with MARG sensors. A gyroscope is used in both CF and GD in order to ascertain orientation. The orientation inaccuracy that is caused by gyro bias drifts may be removed using an accelerometer in conjunction with a magnetometer. However, it is important to note that these approaches do not incorporate system flaws or the measurement noise of the sensors; hence, the accuracy of the estimate is dependent on the inertial and magnetic sensors.

The Kalman Filter (KF) and the Extended Kalman Filter (EKF), both of which are examples of well-known optimum estimate techniques, have found use in a variety of contexts, most notably in the estimation of the attitude of spacecraft (Lefferts E.J., 1982). Sabatini (2012) suggested a typical quaternion-based EKF for the purpose of detecting orientation via the use of 9-DOF sensors. Modeling included ten states, including four-dimensional quaternions, three-dimensional acceleration bias, and three-dimensional magnetic field bias. After constructing the Jacobian matrix, the measurement model was linearized so it could be used. In (Liang Jian-hong, 2012), a cubic polynomial temperature curve was used to correct the gyro, and an EKF based on quaternions was given for the AHRS. This was done so that a better estimate of the gyro bias drifts could be made without making the state vectors bigger. Recent research (Li Wei, 2013, Lee J.K., 2012, and Miao Cun-xiao, 2014) has focused on how to deal with external acceleration or magnetic disturbance, both of which would mess up the orientation estimate a lot. On the other hand, it's important to remember that the typical EKF has to linearize the process models and/or measurement models; this will always result in linearization errors being introduced into the Kalman filter. In addition, the calculation of the Jacobian matrix by microcontrollers is a significant challenge in terms of computing burden.

There have been many different ways created for quaternion-based nonlinear observation in order to prevent linearizing measurement models and lower the amount of computing burden. Bach-man et al. wrote about a better Kalman filter based on quaternions that can track the human body (2006). Using a Gauss-Newton iteration method, accelerometer and magnetometer data were preprocessed to get quaternions, which were then given to the Kalman filter (Marins J.L., 2001). In the paper written by Yun Xiao-ping in 2003, the authors lowered the dimensionality of state vectors by using a reduced-order Gauss-Newton approach that made use of error quaternions. In fact, Wahba's problem can be thought of as an estimation problem in which measurements of vectors are taken at a single point in time. A "single-frame" algorithm is a name for this type of solution. For a Kalman filter based on quaternions, the QUaternion ESTimator (QUEST) method was made. People think that this is one of the best "single-frame" algorithms for quaternions (Yun Xiao-ping, 2006). In order to use the Gauss-Newton method, you would also have to figure out the objective error function's inverse matrix. Because of this, these methods are not good for figuring out the orientation in real time in places where things move quickly, like in a quad rotor.

3. Research Methodology

We suggested that a Kalman filter be built on the ESOQ-2 algorithm. Figure 3 shows how the Kalman filter is made up of its parts. It is clear that the accelerometer and magnetometer readings were sent to the ESOQ-2 algorithm as input vectors to make the observation quaternion. The supply of the quaternion that was created by the ESOQ-2 technique as the observation vector for the Kalman filter helps to simplify the difficult computation by reducing the amount of work that has to be done. In order to prove that E2QKF is effective, we ran few experiments focusing on the motion of the upper arm. This result was superior than the advanced versions of other techniques.

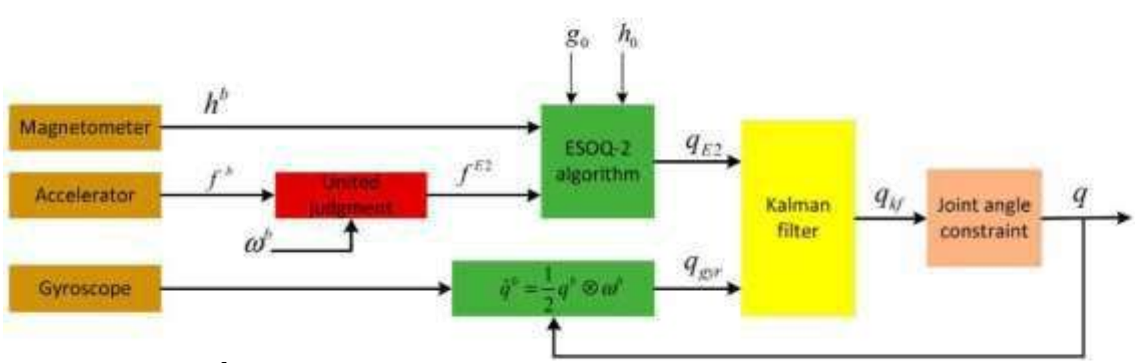


Figure 1 Proposed System

In 1965, the ESOQ -2 algorithm has been suggested as a solution for wabha problem. The essential part of the challenge is to find a solution to the optimum orthogonal matrix with a determinant of one, which will provide the least amount of loss function.

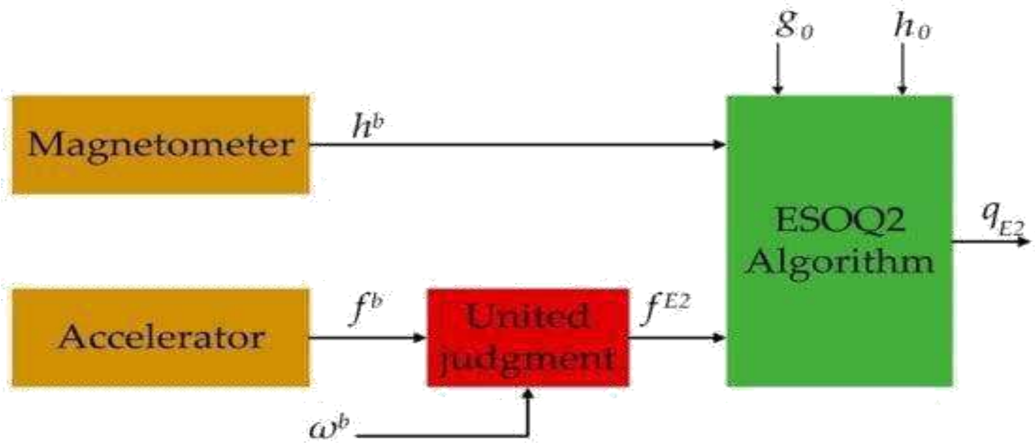
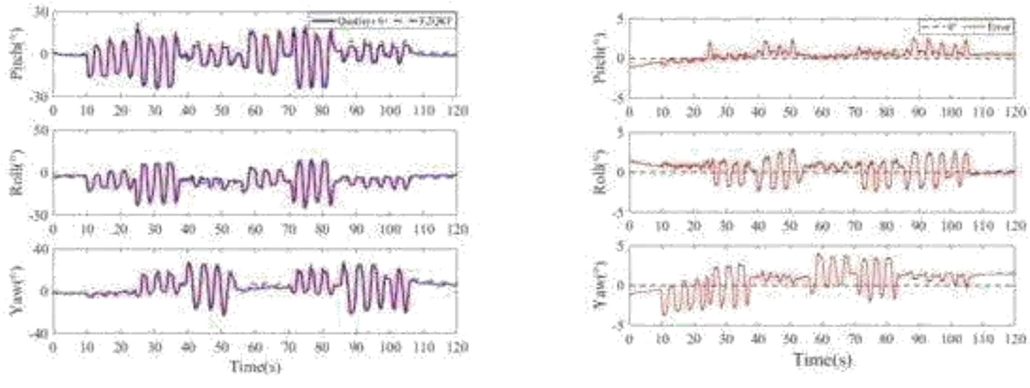


Figure 2 ESOQ-2 algorithm.

Then, we took into consideration that the environment needed to be quasi-static in order to use the ESOQ-2 method, which is a precondition for employing the algorithm. The accelerometer, on the other hand, is sensitive not only to the acceleration caused by gravity but also to the acceleration caused by human body movement. Even when the acceleration of the motion is very modest, the ESOQ-2 algorithm maintains a believable level of accuracy. But if the motion is very dynamic, the ESOQ-2 method won't be as accurate. The state quaternion, on the other hand, will be more accurate. In this case, we looked at how fast the movement was going. When the acceleration of motion is not too great, the accelerometer outputs are used to feed the ESOQ-2 algorithm with the gravity acceleration vector. The input was changed to the vector that was derived using the quaternion that was supplied if the motion acceleration was high.

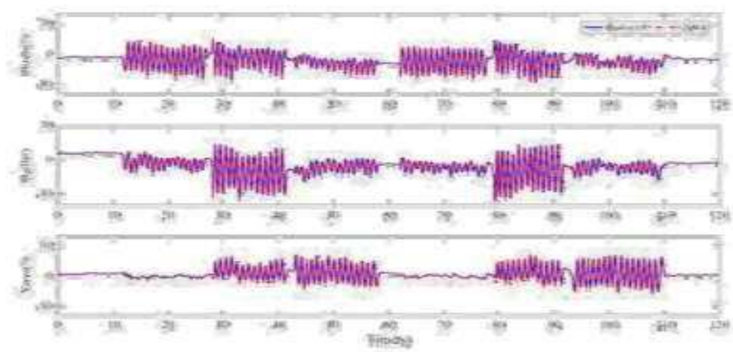
4. Results and Discussion

Measurements of the upper arm according to a typical E2QKF are shown in figures 3a and 3b. These measurements were obtained at a rate of 0.5 steps per second. 0.5 steps = 1 second. The E2QKF readings of the upper arm at a rate of 2 movements per second are shown in figures 12a and 12b. The two tests are presented as a measurement that lasts for a total of one minute and twenty seconds. Between 0 and 10 seconds is the time allotted for the first calibration of the attitude, between 10 and 60 seconds and between 60 and 110 seconds are the times allotted for repeat movements, and between 110 and 120 seconds is the time allotted for the static period. In Figures 3a and 4a, the Euler angles that were estimated by the Oqus 6+ are denoted by the blue solid lines, while the Euler angles that were approximated by applying E2QKF are denoted by the red dotted lines. The Euler angle errors of E2QKF are shown in figures 3b and 4b, respectively.

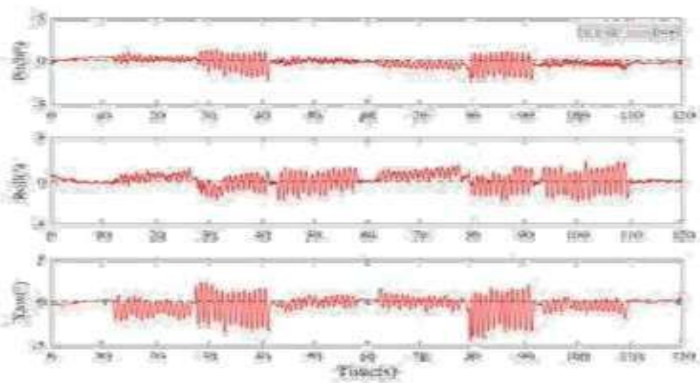


(a) (b)

Figure 4. E2QKF (**a**) The Euler angles (**b**) Euler angle errors.



(a)



(b)

Figure 4. E2QKF (**a**) The Euler angles (**b**) Euler angle errors.

The fact that the Euler angles calculated by E2QKF were quite similar to those calculated by Oqus 6+, as shown in Figures 3a and 4a, demonstrated that E2QKF produced highly accurate results. The Euler angle errors of varied speeds are shown to be consistent within a range of about 5 degrees in both Figure 3b and Figure 4b. This demonstrates that E2QKF is capable of adjusting to various motion speeds. Also, because the object moves the same way from 10 to 60 s and from 60 to 110 s, the error is close to repetition in both of these time periods, and the overall error stays within a certain angle. This showed that the filter could be used to measure long-term human body motion.

5. Conclusion

A new Kalman filter was suggested for figuring out how the human body moves with high accuracy by combining data from inertial and magnetic sensors. The results of this research are presented in the publication. Real-time production of correct orientation estimates of human body motion was the intended purpose behind the development of the Kalman filter, which was created with that objective in mind. The design of the filter takes use of a straightforward linear system model of the first order rather than a complex seven dimensional nonlinear system model. By preprocessing the data through ESOQ-2 technique, the Kalman filter was able to be made substantially more straightforward. The ESOQ-2 algorithm was adjusted to incorporate compensation for the accelerometer in order to make it more accurate in the case that the human body was moving quickly. This was done so that the algorithm would work properly even in the presence of rapid motion. This will make the calculation simpler. Experiments on how the upper arm moves were carried out in order to provide evidence that E2QKF is effective. In addition, we took into consideration the joint angle restriction, which allowed us to get more accurate answers, with an absolute maximum error of less than 3.0 degrees. This was accomplished by using the joint angle limitation as a constraint. In this particular research project, the method known as E2QKF was proposed for the purpose of tracing the motions of the human body. The outcomes of the experiments demonstrated that this method is capable of tracing the motions of the human body in real time and in a variety of different environments. This work has, in the end, provided an explanation of the methodology.

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