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Using frequency analysis to improve the precision of human body posture algorithms based on Kalman filters

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A B S T R A C T

With the advent of miniaturized inertial sensors many systems have been developed within the last decade to study and analyze human motion and posture, specially in the medical field. Data measured by the sensors are usually processed by algorithms based on Kalman Filters in order to estimate the orientation of the body parts under study. These filters traditionally include fixed parameters, such as the process and observation noise variances, whose value has large influence in the overall performance. It has been demonstrated that the optimal value of these parameters differs considerably for different motion intensities. Therefore, in this work, we show that, by applying frequency analysis to determine motion intensity, and varying the formerly fixed parameters accordingly, the overall precision of orientation estimation algorithms can be improved, therefore providing physicians with reliable objective data they can use in their daily practice.

1. Introduction

Measuring human motion in an objective way has great importance in medical applications since it allows for the improvement of diagnosis and treatment of many diseases. It may, for instance, help Medical Doctors to evaluate patients suffering from neurodegenerative diseases which affect the motor system such as Parkison's [15,35]. Moreover, it can be a great aid to increase the efficiency of rehabilitation processes [37], reduce the risk of falls [12], analyze gait [19], study sleep disorders [36] and detect regular [2] and unnoticed nocturnal epileptic seizures [29], among other applications.

Human motion can be assessed and measured in different ways and, consequently, there are different key points which need to be considered when choosing between one of the existing systems and approaches to measure it. The first important factor is to decide the reference point of the measurement system. There exist two possibilities, setting a fixed point in space or including it directly on the moving body. The most common approach of the former is to place special cameras around the area of mobility of the patient under study [4]. These cameras, which act as observers can be based on infrared technology, in which case, they emit infrared light that is reflected on a series of markers worn by the patient [38,30]. On the other hand, a combination of standard cameras and ultrasound technology [22] can be employed to avoid the necessity of covering the patient with markers [5].

Camera-based systems provide accurate measurements but their major drawback lies on the limitation of the range of action and movement of patients to a room. Moreover, they have a reduced flexibility since the system needs to be recalibrated each time one of the cameras is set in a new position. Additionally, complex algorithms need to be applied to extract acceleration and orientation angles from the markers. On the other hand, if we choose to use a reference point on the monitored body, our system will permit performing ambulatory measurements as the subject's motion will not be bound to a room. In this case, we will need a device which is worn by the patient and is able to measure relative acceleration, angular velocity and heading. That is, our system will require acceleration sensors (accelerometers), angular rate sensors (gyroscopes) and magnetic field sensors (magnetometers). These sensors are usually integrated together with other electronic components such as memory units, processors, transceptors, etc., to form Inertial Measurement Units (IMUs) or Magnetic Inertial Measurement Units (MIMUs).

The data that are gathered by the MIMUs usually require from a calibration process to transform raw data into meaningful physical units prior to any further processing. Calibration of inertial sensors is a popular topic and many works propose different techniques and algorithms for such a task [8,16,11,9]. Once the data are

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calibrated, they can be processed to infer the orientation of the body of the patient which is wearing them.

When starting the search of algorithms to estimate body position, orientation and motion, one can be overwhelmed by the vast amount of works published within the last decade. All proposed algorithms share some points in common though, as they all fuse the information coming from all three types of sensors to improve the precision of the estimates when the sensors are used separately.

Additionally, it is worth mentioning that the great majority of approaches rely on the Kalman filter [13,39] to perform such a fusion.

Another common denominator of orientation estimators is given by the fact that they all have a set of tunning parameters which remain constant during the execution and which are of utmost importance to their performance. This set of parameters controls the weight which is given by the filter to the observation when updating the estimation. Usually, in motion monitoring applications which are based on inertial sensors, the measured acceleration is considered as the observation. It is a fact that the estimated orientation is less accurate whenever the intensity of motion is high, that is, the linear acceleration is not negligible with respect to the gravity. Therefore, due to the changing nature of human body motion in terms of intensity, maintaining the same value of these parameters during execution will decrease the accuracy of the orientation estimates. This is due to the fact that the optimal value of the parameters for low and high intensities differs significantly as it was shown in Olivares [23].

In this work, we demonstrate how we can determine different motion intensity levels through the use of frequency analysis, and how we can improve the overall precision of the Kalman Filter by giving different values to its parameters for each intensity level. This strategy (adapting parameters according to motion intensity) is known as gating. More specifically, we will apply two different approaches: one containing two levels of intensity (low and high) and another one containing three levels (low, mild and high) and compare their results with respect to the traditional fixed-parameters version. Additionally, for each one of these approaches, we will study two variations. The first one modifying both Q (process noise covariance matrix) and R (measurement noise variance) parameters, and the second one modifying just R, as suggested in the recent work by Bennett et al. [3].

The remainder of the paper is structured as follows: Section 2 includes a review of the state of the art; next the theoretical background of the frequency-based intensity detector and gated sensor fusion are presented in Section 3; experiments carried out to test the different gated sensor fusion approaches are included in Section 4 and subsequently discussed in Section 5; finally, conclusions and future work are drawn in Section 6.

2. Previous work

2.1. Orientation estimation algorithms

The use of inertial sensors to estimate trajectory and orientation started in the 1970s. NASA scientists begun to develop algorithms to assist the navigation of spaceships and determine their position relative to different reference frames.

An example of these early methods are the TRIAD [14] and the QUEST algorithms [34]. The former algorithm computes a deterministic solution for the orientation using two vector observations, e.g. measured acceleration and magnetic field, and two vector references, e.g. the a priori known gravity and local Earth magnetic field vectors. On the other hand, QUEST is based on the minimization of a loss function in order to calculate the optimal quaternions describing the orientation. In the context of human body analysis, these two algorithms exclusively use acceleration and magnetic field. Therefore, to overcome problems inherent to linear acceleration in intense motion scenarios, [41] fuse the estimates of the QUEST algorithm with integrated angular rate by means of an Extended Kalman Filter.

Different variations of these early approaches have been designed with the last two decades, specially by Shuster [33], Markley and Mortari [21], and Marins et al. [20]. The latter work uses a Gaus–Newton iterative algorithm to compute the quaternion which best relates the gathered acceleration and Earth magnetic field in the body frame to computed values in the earth coordinate frame. The quaternion is, then, subsequently fused with angular rate using an EKF. This configuration provides accurate results but adds, in exchange, high computational complexity as the iterative minimization is computed for every new set of measurements.

Although the use of quaternions is a popular solution to represent orientation, different examples of non-quaternion estimation can still be found in the literature [28].

Further information about nonlinear orientation estimation algorithms is available in Crassidis et al. [6] and a comparative performance study between the most popular approaches can be found in Young [40].

2.2. Estimation of orientation applied to human body position and motion monitoring

The miniaturization of inertial sensors in the form of Microelectromechanical Systems (MEMS) permitted to develop small, light and wearable devices which soon started to be placed on subjects to measure different kinematic parameters.

Many different works have been published in the last 15 years in which inertial sensors are employed to analyze human motion.

Zhang et al. [42] propose a Hybrid Dynamic Bayesian Network to include nonlinear hip angle dynamics in the kinematic model. In addition, a Gaussian Particle Filter to compute the hip angle during gait is employed. The filter is fed with inertial data measured by a device which is worn on the thigh by the subjects.

Luinge et al. [17] describe a method which uses a kinematic model that includes constraints in the elbow nature to estimate the orientation of the forearm with respect to the upper arm. They apply a least squares filter on triaxial acceleration and angular rate to minimize the adduction angle. This method is not accurate enough since the errors can be as high as 40° RMS. In a different work Luinge and Veltink [18], they describe a Kalman filter which, again, only uses acceleration to estimate orientation. In this case, the filter is only tested under quasi-static conditions obtaining an average error of 2° RMS.

Roetenberg et al. [31] present a complementary Kalman Filter to compute the orientation of different body segments through the fusion of acceleration, angular rate and magnetic field. In addition to the orientation, the filter also estimates the gyroscope error bias and the magnetic disturbance error. Their design obtains an static error (low intensity) of 1.4° RMS and a dynamic (high intensity) error of 2.6° RMS.

Favre et al. [7] show two different methods to measure rotation fusing triaxial angular rate and acceleration. The algorithms estimate the orientation quaternion during instants in which the subject is quasi-static and update the estimated value when the subject moves using the gyroscope measurements.

Analogously, Sabatini [32] proposes an algorithm based on an interpolation technique to estimate orientation of the legs during gait. The method provides an average 14.6° RMSE during a single gait cycle and 14.8° RMSE for an extra second cycle. Moreover, the

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