6 DOF Motion Analysis Using Inertial Sensors

Daniel Roetenberg, Henk Luinge and Per Slycke

Xsens Technologies B.V., Enschede, The Netherlands, daniel.roetenberg@xsens.com

Introduction

The use of miniature inertial sensors has become a common practice in ambulatory motion analysis. For accurate and drift free orientation estimation several methods have been reported combining the signals from 3D gyroscopes, accelerometers and magnetometers. Accelerometers are used to determine the direction of the local vertical by sensing acceleration due to gravity. Magnetic sensors provide stability in the horizontal plane by sensing the direction of the earth magnetic field like a compass. Data from these complementary sensors can be used to eliminate drift by continuous correction of the orientation obtained by integrating rate sensor data [1].

By using the calculated orientations of individual body segments and the knowledge about the segment lengths, rotations between segments can be estimated and a position of the segments can be derived under strict assumptions of a linked kinematic chain [2]. This method assumes an articulated rigid body in which the joints only have rotational degrees of freedom. However, a human body and its joints cannot be modeled as a pure kinematic chain with well-defined joints such as hinge-joints and ball-and-socket-joints. Each human joint allows some laxity in all directions (both translational and rotational) other than its main direction of movement [3]. Moreover, to be able to track complex human joints and non-rigid body parts accurately, more than three degrees of freedom, as given by an orientation measurement, are required. Furthermore, importantly, with only orientation driven motion capture, it is not possible to analyze the clearance of both feet, which occurs during running or jumping. Using this approach, it is also not possible to accurately determine the displacement of the body with respect to a coordinate system not fixed to the body.

To provide full six-degree-of-freedom tracking of body segments with connected inertial sensor modules, each body segment's orientation and position can be estimated by, respectively, integrating the gyroscope data and double integrating the accelerometer data in time. However, due to the inherent integration drift, these uncorrected estimates are only accurate within a few seconds.

In this study, a new method is presented to estimate body segment orientation and position by integration of gyroscope and accelerometer signals which are continuously updated by using a biomechanical model of the human body. By facilitating the constraints of the model, notably, the segments are connected by joints, the kinematics of body segments are corrected for drift and other errors. This paper will focus on the joint position update with an example of gait.

Methods

Sensor fusion scheme

The biomechanical model includes the assumption that two body segments are on average connected but with a statistical uncertainty. For specific joints, rotational characteristics can also be described in statistical terms. For example, in the knee, the main axis of rotation is flexion and extension whereas endo rotation and abduction are usually limited to a few degrees and thus statistically more unlikely. Since the sensor signals and the biomechanical model can be described in a stochastic manner, it can be incorporated in a sensor fusion scheme with a prediction and correction step (Figure 1). In the prediction step, all sensor signals are processed using inertial navigation system (INS) algorithms. This is followed by the prediction of the segment kinematics using a known sensor to body alignment and a model of the body. Over time, integration of inertial sensor data leads to errors and increased position uncertainty due to presence of sensor noise, offsets, orientation errors or other errors, e.g. soft tissue artifacts. The correction step includes joint updates, detection of contact points of the body with an external world which constraints the global position and velocity, and optionally, other aiding sensors. Estimated kinematics are fed back to the prediction step to be used in the next frame.

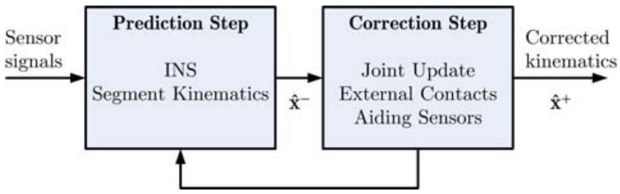

Figure 1. *Sensor fusion scheme. In the prediction step, sensor kinematics are calculated using inertial navigation algorithms (INS) from measured accelerations and angular velocities. Using the biomechanical model, the sensor kinematics are translated to body segment kinematics. In the correction step, joint updates are applied to the segments, followed by the detection of contacts of body points with the external world and optionally aiding sensors.*

Joint update

For each joint, the position relation can be expressed as a linearized function:

$$\mathbf{y}_t = \mathbf{C}\mathbf{x}_t + \mathbf{w}_t$$

where is $\mathbf{x}$ the state vector at time t containing the positions of the two segments, $\mathbf{C}$ is the measurement matrix relating the state vector to the measurement $\mathbf{y}$, $\mathbf{w}$ is the measurement noise. When two segments are connected, measurement matrix $\mathbf{C}$ is given by:

$$\mathbf{C} = [\mathbf{I}_3 \ \ -\mathbf{I}_3]$$

$\mathbf{I}_3$ symbolizes the 3 by 3 identity matrix. A Kalman filter is used to estimate the state using the joint relation and the state prediction by the segment kinematic integration step:

$$\mathbf{x}_t^+ = \mathbf{x}_t^- + \mathbf{K}\,(\mathbf{y}_t - \mathbf{C}\mathbf{x}_t^-)$$

where $\mathbf{x}_t^-$ and $\mathbf{x}_t^+$ are the states before and after the Kalman update, respectively, and $\mathbf{K}$ is the Kalman gain. The Kalman gain is computed based on stochastic parameters about positional and rotational characteristics for each joint and propagation of errors by each integration step based on the sensor noise. With the Kalman filter update, the kinematics are corrected for drift and the uncertainty of the joint position is reduced (Figure 2).

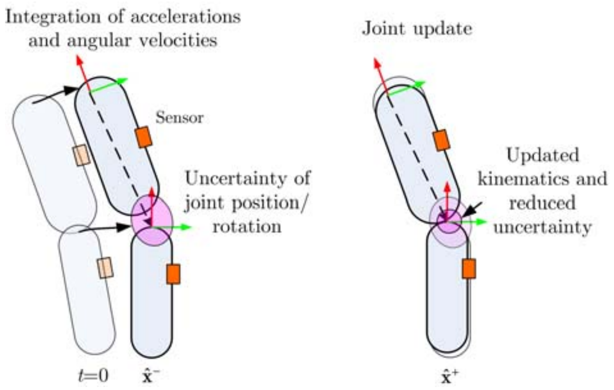

Figure 2. *Integration of accelerations leads to an increased uncertainty about the joint position. After a joint update, the kinematics are corrected and the uncertainty is reduced.*

Experimental set-up

For the experiments, a Moven motion capture system was used consisting of 16 MTx sensors with two Xbus Masters running at 100 Hz [4]. The MTx is an inertial and magnetic measurement unit and comprises 3D gyroscopes, 3D accelerometers and 3D magnetometers (38×53×21 mm, 30 g). For the analysis of the data, the sensors on the feet, lower legs, upper legs and pelvis were used. No magnetometer signals were used.

One healthy subject was asked to walk at a comfortable speed for 10 meters in an office corridor. Data was processed using a translational laxity of the hip joint with a SD of 1cm.

Results

In Figure 3, the kinematics of 2 complete gait cycles are presented. The upper graph shows the position of the hip joint in the global reference frame. The accuracy in position of the foot was 0.19 m after 10 meters. Walking speed was 1.2 m/s. The second graph shows the hip flexion/ extension angle. The dotted lines indicate the standard deviation band of a reference hip angle database of normal walking [5]. The vertical black dashed lines indicate the heel strike events, the red dotted lines the toe off events. These gait cycle events were detected using kinematic properties of the foot, such as height, velocity and acceleration. The third and lower graph shows the estimated movement of the head of the femur within the hip joint of the joint by using the joint update.

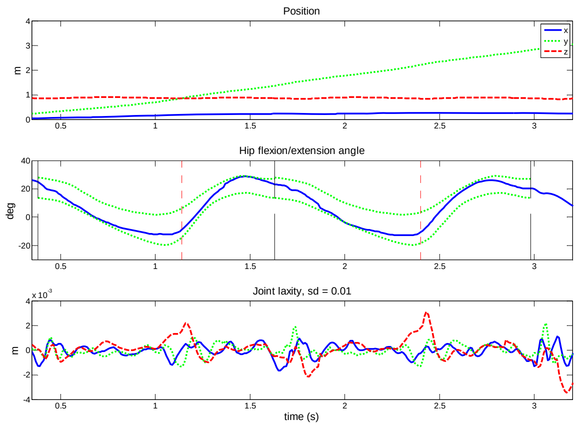

Figure 3. *Kinematics of 2 gait cycles.*

Discussion

The results show the feasibility of using inertial sensors in combination with joint updates to estimate drift-free 3D kinematics. The translation accuracy is within 2% of the travelled distance. Hip flexion and extension angles show a pattern which is similar to a reference gait database.

The observed movement within the joint is mostly due to soft tissue artifacts of the upper leg. As a result, position and orientation changes in the segments around the joint can be measured which are biomechanically unlikely. In the joint update step, the allowed laxity can be set according to rotational and translational parameters as known from literature. Measured motion beyond these values is most likely due to soft tissue artifacts. Therefore, these errors can be reduced.

In processing the data, no magnetometers were used. For longer trials, magnetometers are necessary to provide stability for rotations about the vertical. However, metallic objects can locally disturb the earth magnetic field introducing errors. By using a disturbance model, similar to [1] and rotational constraints in the joint update step, these errors can be minimized.

Since the inertial data can be used accurately for position changes, the presented method allows for dynamic motion analysis including clearance of both feet.

References

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