Online Tracking of the Lower Body Joint Angles using IMUs for Gait Rehabilitation

Vladimir Joukov, Michelle Karg, Dana Kulić
Electrical and Computer Engineering
University of Waterloo, Ontario, Canada

***Abstract*— An important field in physiotherapy is the rehabilitation of gait. A continuous assessment and progress tracking of a patient's ability to walk is of clinical interest. Unfortunately the tools available to the therapists are very time-consuming and subjective. Non-intrusive, small, wearable, wireless sensors can be worn by the patients and provide inertial measurements to estimate the pose of the lower body during walking. For this purpose, we propose two different kinematic models of the human lower body. We use an Extended Kalman Filter to estimate the joint angles and show that a variety of sensors, such as accelerometers, gyroscopes, and motion capture markers, can be used and fused together to aid the joint angle estimate. The algorithm is validated on gait data collected from healthy participants.**

I. Introduction

Human pose estimation is useful in multiple fields, including the film industry, sports bio-mechanics, and physical rehab. Currently in rehabilitation the initial assessment of the patient is, for the most part, qualitative and subjective. The therapists have access to only rudimentary tools such as goniometry, a technique for measuring a single human joint angle that cannot be used when the patient is in motion. After the initial assessment, the therapists need to track patient progress and make sure that all assigned exercises are done properly. The latter is particularly difficult since a therapist may have to supervise multiple patients at a time and often the patients are assigned exercises to perform on their own.

In this research, we aim to develop a system which will accurately estimate the patient's lower body kinematics (positions, velocities, and accelerations of the joint angles) using small, non-intrusive inertial measurement units (IMU). Providing continuous pose measures during gait rehabilitation enables the physiotherapist to extract objective measures including range of motion, stride length, and number of strides. In a study comparing different sensors available for physiotherapy applications, IMUs were shown to be the most preferable solution due to their compact size and low cost [1]. Also, IMUs allow multiple patients to be in close proximity since they do not rely on cameras and are not subject to occlusion problems.

Several existing works have used IMUs to estimate human joint angles. However, often they focus on a specific joint or make restrictions on the allowed motion. Bergmann *et al.* used accelerometers to estimate the knee joint angle, but made the assumption that motion was slow enough for centripetal acceleration to be negligible and only in one plane. The results were shown to be close to that of a motion capture system with visual markers, but when the motion is fast, centripetal acceleration causes large errors [2].

Schwarz *et al.* proposed a learning approach to estimate full body joint angles from IMU measurements [3]. They used a motion capture studio to record joint angles and sensor data then applied Gaussian Process Regression to learn a global mapping between sensor measurements and the joint angles of different activities. To determine which activity mapping should be used on new sensor data they applied a multi-class Support Vector Machine. While the results of this approach are close to those obtained with optical motion capture, it is not suitable for rehabilitation applications since per-person training is required to find the mapping between IMU measurements and joint angles.

Zhou and Hu proposed using Extended Kalman Filter (EKF) and inverse kinematics to estimate the position of the elbow and wrist with an IMU attached at the wrist [4]. This approach does not include joint angle estimation from IMU measurements or a multiple DOF kinematics model. Lin and Kulić proposed an approach using EKF and a multiple DOF kinematic model to estimate position, velocity, and acceleration of the joint angles of one leg. The state vector of the EKF contained the joint angles, velocities, and accelerations and the measurement vector was composed of accelerometer and gyroscope readings provided by sensors attached above the knee and ankle [5]. This approach is evaluated on several rehabilitation exercises where the base frame of the kinematic model is fixed, e. g., seated leg exercises. When the fixed base frame assumption is valid, the estimation of joint angles from IMU measures is comparable to the performance of optical motion capture.

In physiotherapy, recovering the ability to walk independently is important to the patients and is a major focus in post-stroke rehabilitation. A device that continuously monitors gait throughout the physiotherapy sessions provides objective measures of gait characteristics that are relevant for planning patient-specific exercise regimens, evaluating the efficiency of exercises, and providing feedback on progress to the patients. The contribution of this study is an extension of Lin's method to monitor gait. This requires considering both legs in the kinematic model and removing the stationary base assumption. With a moving base, we are able to extract not only the joint angles but Cartesian trajectories as well, (e.g. for computing gait symmetry measures, stride length,

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

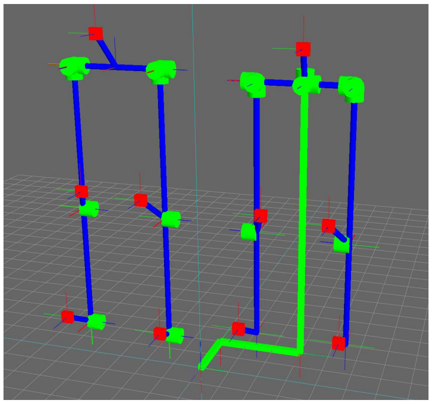

Fig. 1. Two proposed kinematic models for human lover body. Blue line segments, red boxes, green cylinders, and green line segments, represent links, sensors, revolute joints, and prismatic joints, receptively. Switching base model (left) with single DOF at the ankles and knees and three DOF at the hips. Prismatic-Revolute model (right), the transformation from world frame and the base frame is described using 3 prismatic and 3 revolute joints, the hips are modeled with 3 DOF and the knees with 1 DOF.

and foot placement). We propose two different methods to overcome the limitation of a stationary base. One allows each leg to act independently, the other works particularly well with IMUs since it does not allow measurement errors to cause divergence in position. In section II, we describe the two different methods for modeling the lower body and using Extended Kalman Filter to estimate the joint angles from IMU sensor measurements. Section III summarizes the experimental results and Section IV concludes with a discussion of the benefits and drawbacks of the two modeling methods and our proposed approach.

II. Proposed Approach

An estimate of the lower body pose is calculated using data from several IMU sensors. The IMU data is combined using EKF to determine the joint angles of a kinematic model representing the lower body.

A. Lower Body Kinematic Model

The human lower body is modeled using branched kinematics. One IMU sensor is attached at the waist, knee, and ankle. In order to overcome the limitation of a stationary base, we propose two different approaches. The first models the movement of the base in the world frame using 3 prismatic and 3 revolute joints, while second switches the base to alternating ankles as the demonstrator walks. The two different models are visualized in figure 1.

1) Prismatic-Revolute Base Model: A transformation from the world frame into the kinematic model's base frame can be expressed as a translation and rotation in each of the world axes *(x,y,z)*. Similarly, both linear and angular velocity and acceleration of the base frame can be represented as velocity and acceleration in the world axis. Thus, it is possible to model a moving base kinematic chain as a fixed base kinematic chain starting with 3 prismatic and 3 revolute joints in the world frame. To fully encompass lower body motion we consider the pelvis as the base, the hips and knees are modeled using three and one revolute joints respectively. This model allows each leg to act independently and thus errors in joint angle estimation in one leg should not affect the other. However it is not bound to the observable region, accumulating position error in the first three prismatic joints will cause the position of the base to diverge.

2) Switching Base Model: A different approach to overcome the limitation of a stationary base is inspired by the characteristic of gait where one leg is the support leg and the other leg is the swing leg. The center of the ankle of the support leg can be considered as the base and the base switches to the other leg when ground contact of the recent swing leg is detected. Adding a single revolute joint at the ankle to the knee joint and the three hip joints allows us to capture full human motion. This model is bound in the observable region and has fewer degrees of freedom. Heel strike detection must be implemented to trigger the base switching. This is done by looking at the accelerometer data of the ankle IMUs, a heel strike results in a large deceleration.

B. Extended Kalman Filter for Kinematic Chain

The Kalman Filter [6] is a popular sensor fusion technique that estimates the state of a system from noisy observations. For a linear model, it is shown to be an optimal filter under the assumption that both measurement and process noise are zero-mean Gaussian.

For a non linear system,the Extended Kalman Filter is used which linearizes the equations about the operating point and the equations are approximated as

$$\mathbf{z_t} \approx \mathbf{\tilde{z}_t} + \mathbf{C}(\mathbf{s_t} - \mathbf{\tilde{s}_t}) + \mathbf{v_t} \tag{1}$$

$$\mathbf{s_t} \approx \mathbf{\tilde{s}_t} + \mathbf{A}(\mathbf{s_t} - \mathbf{\tilde{s}_t}) + \mathbf{w_{t-1}}, \tag{2}$$

where $\mathbf{A}$ and $\mathbf{C}$ are the Jacobians of the state update and measurement equations with respect to the state $\mathbf{s}$, $\mathbf{\tilde{s}}$ is the noiseless state estimate, $\mathbf{\tilde{z}}$ is the noiseless measurement estimate, v_t is the measurement noise, and w_{t-1} is the process noise [6]. For our purposes, the state vector consists of the position $\mathbf{q}$, velocity $\mathbf{\dot{q}}$, and acceleration $\mathbf{\ddot{q}}$ of the joint angles and the measurement vector includes the IMU sensor readings.

Position $\mathbf{q}$, velocity $\mathbf{\dot{q}}$, and acceleration $\mathbf{\ddot{q}}$ of the joint angles can be described by a continuous function, where their values at the next time-step are predicted by integrating the velocity and acceleration terms [5]. Any change in the acceleration is assumed to be part of the noise:

$$\mathbf{q_t} = \mathbf{q_{t-1}} + \mathbf{\dot{q}}\Delta t + \mathbf{\ddot{q}}\Delta t^2/2 \tag{3}$$

$$\mathbf{\dot{q}_t} = \mathbf{\dot{q}_{t-1}} + \mathbf{\ddot{q}}\Delta t \tag{4}$$

$$\mathbf{\ddot{q}_t} = \mathbf{\ddot{q}_{t-1}}, \tag{5}$$

where Δt is the time difference between each measurement.

By considering the sensors as end effectors of the kinematic chain, the measurement prediction is done using forward kinematics and the derivative of the measurement equation with respect to the state becomes a combination of standard Jacobians used in robotics [7].The Jacobians for gyroscope and accelerometer measures are:

1) Gyroscope: A gyroscope sensor measures the rate of rotation around its internal frame. Rate of rotation for an end effector in a kinematic chain can be expressed as $\mathbf{w} = \mathbf{J_w}\dot{\mathbf{q}}$, where J_w is the angular Jacobian in the end effector frame. Thus the observation Jacobian in the EKF is

$$\mathbf{J_{gyro}} = \begin{bmatrix} 0 & \mathbf{J_w} & 0 \end{bmatrix}. \tag{6}$$

2) Accelerometer: An accelerometer measures the acceleration in the sensor's frame including gravity. Acceleration applied to the sensor from the kinematic chain is a combination of centripetal acceleration due to the velocity of revolute joints $\dot{q}$ and tangential acceleration due to the joint accelerations $\ddot{q}$. We can express the combined acceleration by using the velocity Jacobian, its derivative, and the gravity vector in the sensor frame:

$$\mathbf{a} = \mathbf{R_0^{sens}}\mathbf{g} + \dot{\mathbf{J_v}}\dot{\mathbf{q}} + \mathbf{J_v}\ddot{\mathbf{q}}, \tag{7}$$

where $\mathbf{R_0^{sens}}$ is the rotation matrix from the world frame into sensor frame and $\mathbf{g} = \begin{bmatrix} 0 & 0 & 9.81 \end{bmatrix}$ is the gravity vector. Taking the derivative of (7) with respect to the state variables results in an observation Jacobian for the accelerometer

$$\mathbf{J_{accel}} = \begin{bmatrix} \frac{\mathbf{dR_0^{sens}}}{\mathbf{dq}}\mathbf{g} & \dot{\mathbf{J_v}} & \mathbf{J_v} \end{bmatrix}, \tag{8}$$

and $\frac{\mathbf{dR_0^{sens}}}{\mathbf{dq}}$ can be expressed with respect to each joint $\mathbf{q_i}$ through skew symmetric matrices and the rotation matrix to the joint frame $\mathbf{R_0^i}$:

$$\frac{\mathbf{dR_0^{sens}}}{\mathbf{dq_i}} = \mathbf{R_0^i}\mathbf{S}(\mathbf{k})\mathbf{R_i^{sens}}. \tag{9}$$

For the Prismatic-Revolute model, EKF can be applied directly by adding the position $\mathbf{q}$, velocity $\dot{\mathbf{q}}$, and acceleration $\ddot{\mathbf{q}}$ of the three prismatic and three revolute joints describing the motion of the base to the state vector. For the Switching Base model the state vector remains as the position $\mathbf{q}$, velocity $\dot{\mathbf{q}}$, and acceleration $\ddot{\mathbf{q}}$ of the joints in the kinematic model. However when the base is switched (i.e. when a heel strike is detected) the kinematic chain reverses, because of this the covariance estimate $\mathbf{P}$ of the EKF becomes invalid. To overcome this problem, we keep track of two covariance matrices: $\mathbf{P_{left}}$ for when left ankle is the base of the kinematic chain and $\mathbf{P_{right}}$ for the right. When a step is detected, the error covariance $\mathbf{P}$ is switched to the appropriate matrix. It is also important to appropriately select the covariance for both the process $\mathbf{Q}$ and measurement noise $\mathbf{R}$. While the sensor noise can be measured, there is no way to measure the process noise and those parameters are selected by experience. In our experiments, the process noise at each joint was set as $0.01, 0.1, 1$ for position, velocity, and acceleration respectively. The measurement noise was set to $5rad/s, 250m/s^2$ for each axis of the gyroscope and accelerometer respectively.

III. Experimental Results

To test the accuracy of the proposed algorithm, the estimated pose was compared to motion capture data.

A. Data Collection

Gait data of 5 healthy participants, ages 19 to 25, was collected. The SHIMMER IMUs were used to collect gyroscope and accelerator measurements. These sensors sample the on-board Freescale MMA7361L 3D accelerometer and two InvenSense 2D IDG-500 gyroscopes to obtain acceleration and rate of rotation about the 3 internal axes [8]. Calibration software from Shimmer Research based on Parvis and Ferraris [9] was used to calibrate the sensors. Motion capture markers were placed on the ankles, knees, and hips as well as on each of the IMUs. Due to the limited size of the motion capture studio it was not possible to capture continuous gait, thus each participant completed two full gait cycles 10 times.

B. Preprocessing

To successfully run the algorithm we need an accurate lower body model of the participant. Using the average distance between motion capture markers during the exercise, we calculate the hip to hip, hip to knee, and knee to ankle lengths as well as the IMU offsets for the kinematic model. Due to human physiology, when each IMU is attached using Velcro straps it experiences slight rotation away from the link. We find the 100 sample window with the least accelerometer variance while the participant is standing still and calculate the rotation matrix between the IMU's gravity vector and world gravity vector g. This rotation matrix is used to align the IMU's frame with the link frame in the kinematic model. Since gyroscopes are known to have drift present in their measurement we also use the window of least variance to compute the gyroscope offset for each of the sensors. Step detection was done manually by looking at the ankle accelerometer signal, the regions affected by the heel strikes were replaced with spline interpolation.

C. Results

To compare the joint angles estimated by the proposed approach with the mocap data, the knee joint angles are computed from motion capture data by looking at the cross product of the vectors formed by the offsets between hip to knee $\vec{a}$, and knee to ankle $\vec{b}$ markers.

$$\theta = sin^{-1}(\frac{\vec{a} \times \vec{b}}{\|\vec{a}\|\|\vec{b}\|}) \tag{10}$$

Figure 2 shows the Switching Base model performance at estimating the knee joint angles for a short walk. The RMSE error in knee angle for both approaches is shown in Table I. We also compared the Cartesian positions of the ankles and knees. Gait features such as stride length and foot placement can be calculated per step. Thus error was considered as zero at the start of each step cycle. Due to the difference in modeling of the legs (independent in the Prismatic-Revolute model and dependent in the Switching Base model), it was important to consider the support and swing leg performance separately. Because the ankle is bound in the Switching Base model, noise in the IMU measurements cannot greatly affect the support leg. However due to the dependence of the legs the swing leg's position error is increased. The

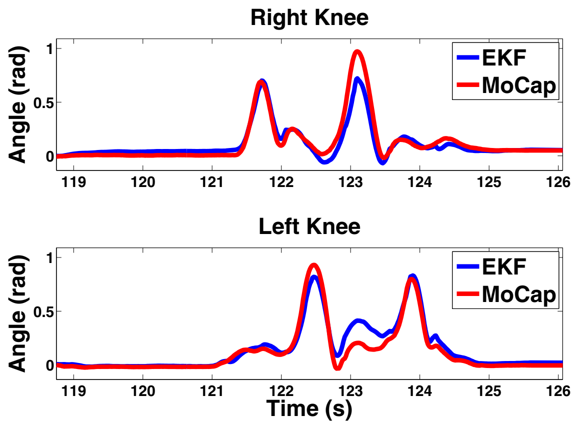

Fig. 2. Comparison between the knee joint angles over two full gait cycles estimated from the motion capture studio (red) and by the Switching Base model EKF (blue).

joint angle and position estimation root mean squared errors are summarized in table I. As expected, we see that the Switching Base model estimates the position much better for the support leg and the Prismatic-Revolute model slightly outperforms in estimating the position of the swing leg.

D. Sources of Error

A major source of error in our experiment can be attributed to the sensors and their attachment to the participant. The IMUs are secured using elastic straps, during a heel strike the strap allows the knee and ankle sensors to continue rotating forward. The EKF estimates this as rotation at the hip joint and causes a characteristic under-step. Other sources of error include modeling the joints at marker locations instead of anatomically correct locations and excluding the ankle to heel distance for the Switching Base model.

TABLE I

ROOT MEAN SQUARED ERROR OF KNEE JOINT ANGLE (ANG) AND CARTESIAN POSITION ESTIMATION USING THE TWO PROPOSED KINEMATIC MODELS. THE CARTESIAN RESULTS ARE SHOWN FOR KNEE (K) AND ANKLE (A) OF EACH LEG (LEFT (L) AND RIGHT (R)) FOR THE SUPPORT (SU) AND SWING (SW) PHASE

	Switching Base Model			Prismatic-Revolute Model		
L K Ang	5.03±1.27 (deg)			5.64±2.12 (deg)		
R K Ang	6.20±1.48 (deg)			6.46±2.37 (deg)		
	x (cm)	y (cm)	z (cm)	x (cm)	y (cm)	z (cm)
L A Su	1.3±1.0	0.3±0.1	0.6±0.3	10.5±1.7	5.6±1.4	3.1±1.4
L A Sw	9.4±2.5	11.9±2.3	9.5±1.3	9.1±3.7	8.5±2.2	8.9±1.9
R A Su	1.0±0.5	0.3±0.1	0.9±0.4	10.6±2.5	5.4±1.6	4.1±0.5
R A Sw	9.9±3.8	8.2±2.2	5.3±1.2	8.1±3.4	5.3±1.6	6.5±1.6
L K Su	3.4±1.6	1.3±0.4	0.9±0.3	5.5±0.7	3.6±0.7	2.4±1.0
L K Sw	6.7±1.7	10.3±2.6	5.2±0.6	7.2±2.7	6.4±2.8	4.0±1.1
R K Su	3.3±1.1	4.1±1.4	1.4±0.6	5.6±0.7	3.4±1.0	2.6±0.9
R K Sw	6.5±2.6	4.4±1.2	2.3±0.6	5.3±1.9	3.3±1.2	2.0±0.9

IV. DISCUSSION AND CONCLUSION

We presented two different approaches for using kinematic chains to model the human lower body and described how EKF can be used to estimate the joint angle positions, velocities, and accelerations for these models. The first approach describes the transformation from world frame to the base frame as three prismatic and revolute joints. The second approach relies on switching the base of the kinematic model when a heel strike is detected.

A major benefit of the first approach is that the movement of the base is built into the model. Thus, it is only necessary to estimate the joint angles, velocities, and accelerations to fully describe how the patient is moving. However, the extra joints needed to represent the moving base introduce additional uncertainty. Also, this model is not bounded so if there is an error in velocity or acceleration in the first three prismatic joints and integration is used to position the model in 3d space the errors will quickly accumulate causing the model to move out of the observable region. This can be overcome by including an additional position sensor. In our experiments, we added an a optical motion capture marker attached to the waist IMU as part of our measurement vector.

Since the second approach binds the model to the floor, measurement errors do not cause it to exit the observable region and it provides more accurate results when only IMU sensors are used avoiding the need for additional position sensors. This model also has less uncertainty due to a smaller number of degrees of freedom. The main drawback is that a step detection algorithm needs to be employed.

Future work will include improving the process model for a specific exercise, learning the EKF noise parameters, and evaluation on patient data.

ACKNOWLEDGMENT

The authors wish to thank Dr. Mitchell Fergenbaum for his advice and feedback regarding rehabilitation and physical therapy. The authors would also like to thank the creators of Robotics Library [10] whose help and quick responses were invaluable during implementation of this work.

REFERENCES

[1] Zhou and Hu, "Human motion tracking for rehabilitationa survey," *Biomedical Signal Processing and Control*, vol. 3, no. 1, pp. 1–18, 2008.
[2] Bergmann, Mayagoitia, and Smith, "A portable system for collecting anatomical joint angles during stair ascent: a comparison with an optical tracking device," *Dynamic Medicine*, vol. 8, no. 1, p. 3, 2009.
[3] Schwarz, Mateus, and Navab, "Discriminative human full-body pose estimation from wearable inertial sensor data," in *Modelling the Physiological Human*. Springer, 2009, pp. 159–172.
[4] Zhou and Hu, "Kinematic model aided inertial motion tracking of human upper limb," in *Information Acquisition, 2005 IEEE International Conference on*. IEEE, 2005, pp. 6–pp.
[5] Lin and Kulić, "Human pose recovery using wireless inertial measurement units," *Physiol. Meas.*, vol. 33, no. 12, p. 2099, 2012.
[6] Welch and Bishop, "An introduction to the kalman filter."
[7] Bruyninckx and De Schutter, "Symbolic differentiation of the velocity mapping for a serial kinematic chain," *Mechanism and machine theory*, vol. 31, no. 2, pp. 135–148, 1996.
[8] Burns, Greene, McGrath *et al.*, "Shimmer–a wireless sensor platform for noninvasive biomedical research," *Sensors Journal, IEEE*, vol. 10, no. 9, pp. 1527–1534, 2010.
[9] Parvis and Ferraris, "Procedure for effortless in-field calibration of three-axial rate gyro and accelerometers," *Sensors and Materials*, vol. 7, no. 5, pp. 311–330, 1995.
[10] Rickert, "Efficient motion planning for intuitive task execution in modular manipulation systems dissertation," Ph.D. dissertation, Technische Universitt Mnchen, 2011.