Human Gait Monitoring Using Body-Worn Inertial Sensors and Kinematic Modelling

Amin Ahmadi, François Destelle,
David Monaghan, Kieran Moran, Noel E. O'Connor
Insight Centre for Data Analytics
Dublin City University, Ireland

Luis Unzueta, Maria Teresa Linaza
Vicomtech-IK4, Paseo Mikeletegi 57, Parque Tecnológico
20009 Donostia, Spain

Abstract—**In this paper, we present a low-cost computationally efficient method to accurately assess Gait by monitoring the 3D trajectory of the lower limb (i.e. 3 segments - foot, tibia and thigh, and 2 joints - ankle and knee). Our method utilises a network of miniaturized wireless inertial sensors, coupled with a suite of sophisticated real-time analysis algorithms and can operate in any unconstrained environment. Firstly, we adopt a modified computationally-efficient, highly accurate and real-time gradient descent algorithm to obtain the 3D orientation of each of the 3 segments. Secondly, by utilising the foot sensor, we successfully detect the stance phase of the human gait cycle, which allows us to obtain drift-free velocity and the 3D position of the foot during functional phases of a gait cycle (i.e. heel strike to heel strike). Thirdly, by setting the foot segment as the root node we calculate the 3D orientation and position of the other 2 segments as well as the ankle and knee joints. Finally, we employ a customised kinematic model adjustment technique to ensure that the motion is coherent with human biomechanical behaviour of the leg. Our method is low-cost, is robust to measurement drift and can accurately monitor human gait outside the lab in any unconstrained environment.**

I. Introduction

The advancement of sensor manufacturing, or computer microminiaturisation, in recent times is a continuing driver of research into a wide variety of scientific fields including the Internet-of-Things. The Internet-of-Things is an area where a network of interconnected sensors, electronics and software can transfer data and has mainly come about through the availability of new low-cost sensors that may be embedded into everyday items. This increasing availability of low-cost sensors is also having a major influence on the field of biomechanical gait analysis.

We can define gait analysis as the systematic study of human walking (locomotion) [1]. An accurate gait analysis is extremely useful for athletes, both professional and amateur, and also for the general population in order to assess and treat individuals with conditions that affect their ability to walk and their entire muscular skeletal system. Traditionally, gait analysis involved a human observer monitoring a subject but this was subsequently augmented with video recording, where the recording could be reviewed in slow motion to allow a more accurate assessment of the gait cycle. The approach is still widely used today, and produces extremely accurate results. However, this method is labour intensive and requires a highly trained sports-scientist or clinician.

Real-time Motion Capture (MoCap) technology used with video can produce more accurate data and allow for a more in depth analysis of gait. This can provide the clinician with a large amount of quantitative biomechanical data, important in assessing joint orientation, acceleration and relative position. MoCap is a field of science that primarily deals with the recording, reconstructing and analysis of motion, and is a well-studied and broad area of research [2]. MopCap can be segmented into two approaches: (1) Marker-based motion capture systems, (2) Markerless-based systems. Marker based MoCap generally represents the gold-standard and offers excellent results but carries a restrictively high price tag and requires post-processing, leaving it out of reach for the general public. For this reason, significant research has been performed into the area of low-cost alternatives, using either markerless based methods such as computer vision based analysis or body worn devices. Whereas many markerless systems suffer from tracking errors due to marker occlusions, Inertial Measurement Units (IMU) offer an accurate MoCap alternative and have been developed into commercial systems, such as Xsens (www.xsens.com). However, many of these systems are prone to drift in accuracy over time, a common limitation of inertial sensors. IMUs are low power, light weight, offer high sample rates and do not suffer from occlusions, but they are susceptible to orientation and position errors if not corrected over time. Furthermore, commercially available IMU MoCap solutions are still relatively high in price (approx. 50K Euro).

In this paper we present a truly low-cost platform that is comprised of 3 low-cost, readily available IMU sensors together with advanced analysis algorithms, multiple IMU automatic calibration algorithms and inverse kinematics analysis. Furthermore, our system contains stance-phase detection, which reduces the integration drift error of the velocity in the IMUs.

II. Proposed Framework

The main components of our framework are illustrated in Fig. 1. It consists of four main components, which are: (1) orientation estimation; (2) foot position estimation; (3) 3D reconstruction; and (4) kinematic model adjustment. Each component is presented and discussed in Section III.

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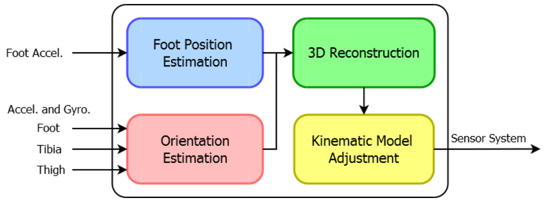

Fig. 1. The main components of the proposed framework.

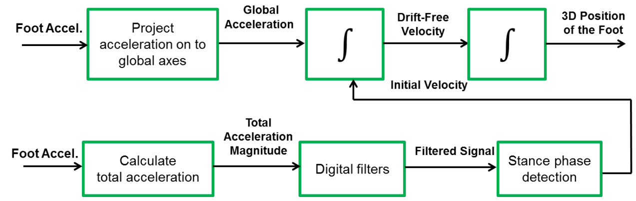

Fig. 3. Overview of the foot position estimation process.

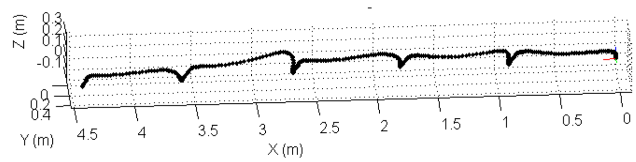

Fig. 4. Calculated 3D position of the foot sensor with respect to the global frame.

III. Methodology

A. Data Collection

Data were collected using three wearable inertial sensors (x-IMU, x-io Technologies, UK) positioned on the participants' foot, tibia and thigh, as seen in Fig. 2. The x-axes were aligned with the longitudinal axes of the body segments. An internal SD card was used to store data from each sensor at 256Hz. A physical event (5 stiff jumps to generate high impact accelerations simultaneously in all sensors at the start and end of the walking trial) was used to temporally synchronize the sensors.

B. Orientation Estimation

We employed a customised gradient descent optimization algorithm, which has been shown to provide effective performance at low computational expense. This algorithm is capable of computing an error based on an analytically derived Jacobean that results in a significant reduction in the computation load [3], [4]. This technique was developed to estimate the sensor orientation with respect to the earth frame during the entire gait cycle. The static and dynamic RMS errors of the orientation estimation algorithm are $< 0.8°$ and $< 1.7°$ respectively, thus achieving an accuracy level matching that of the Kalman based algorithm [3], [4].

C. Position Estimation

Human gait motion is a cyclic motion consisting of two main phases, the stance phase where the foot is in contact with the ground and the swing phase where the foot is traversing from one stance phase to the next. With precisely accurate IMUs a double integration of the acceleration data yields accurate 3D position. However, IMUs have small errors in acceleration and thus the position estimates based upon a double integration technique can only be valid for a short period of time as these small errors are accumulative and lead to 3D position drift. Our method obtains accurate 3D position while using the double integration technique by correcting the drift error at each stance phase [4], [5]. During the stance phase, the magnitude of the acceleration of the sensor attached on the foot is expected to be very small (it is non-zero but it is lower than an experimentally obtained threshold). Once the stance phase is successfully detected, the velocity can be corrected during that phase (i.e. initial velocity is set to zero) and subsequently the 3D position of the foot during the swing phase can be calculated [6]. The overview of the 3D foot position estimation is illustrated in Fig. 3 and the calculated 3D position of the foot sensor with respect to the global frame is illustrated in Fig. 4.

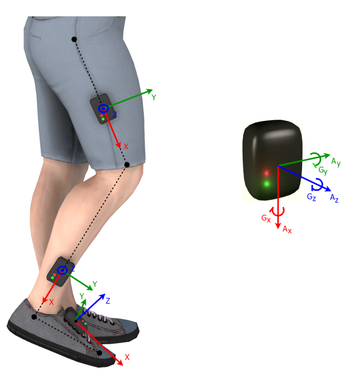

Fig. 2. Placement of inertial sensor units.

D. 3D Reconstruction

We aim to animate a skeletal model only from the estimation of the ankle position and the changes in local orientation from each sensor. A fixed skeleton of reference is used to tackle the lack of complete global information. This skeleton is modelled by a stick figure, see Fig. 5(a). It assumes a perfect standing pose at the beginning: the leg is vertical and the foot is horizontal pointing in front of the model. Relative to our specific sensor placement (see Fig. 2), the front direction is aligned with the direction $X : \{1, 0, 0\}$ of our global coordinates system. This geometrical reference is then animated using only the ankle position and the rotational estimations of the three sensors in a hierarchical manner as depicted in Fig. 5(b-e). This 3D reconstruction approach uses a very similar method presented in [7], using here the lower part of the subject's body. In this study we have restricted our 3D reconstruction to one leg but extension to reconstruct two legs is trivial.

1) Initial Skeleton of Reference: We consider for one leg the set of joints positions for a sequence frame t as $p^t : \{p^t_a, p^t_f, p^t_k, p^t_h\}$, respectively the position of the ankle, the foot, the knee and the hip. The virtual ankle position can be calculated using the calculated 3D foot position described

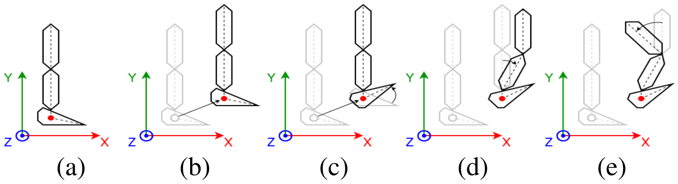

Fig. 5. Diagram of the 3D gait reconstruction method: (a) We start from the first frame of the sequence, the first one being our fixed reference. (b) All the joints are translated relatively to our evaluation of the ankle displacement. (c) We then rotate the foot segment relative to the foot sensor orientation. In a hierarchical manner, we then rotate the tibia (d) inducing the new thigh position. (e) Lastly we rotate the thigh segment with respect to the orientation of the thigh sensor, inducing the final hip joint position.

in section III-C. Let the initial position of each skeleton joint to be $p_0 : \{p_a^0, p_f^0, p_k^0, p_h^0\}$. Also the length of the foot l_f, tibia l_k and thigh l_t need to be accurately measured prior to reconstructing the leg.

2) Animation of the Reconstruction over Time: The first step of the animation algorithm at frame t is to update the ankle joint position by using the previous frame p_a^{t-1}. All the remaining joint positions are then translated from their initial positions to new ones relative to the new ankle joint position. In the next step, the foot and ankle orientations are updated utilizing the estimated 3D orientation of the foot sensor. then the tibia segment is rotated using the estimated orientation of the tibia sensor. This results in generating new positions for the knee and hip joints. Finally the thigh segment orientation is updated using the estimated orientation of the thigh sensor and leads to the final position of the hip joint. The reconstructed skeleton is evaluated for a frame t using:

$$\begin{cases} p_f^t = p_a^t + q_a^t \otimes (\ l_f X\ ) \otimes \overline{q_a^t} \\ p_k^t = p_a^t + q_k^t \otimes (\ l_k Y\ ) \otimes \overline{q_k^t} \\ p_h^t = p_k^t + q_h^t \otimes (\ l_t Y\ ) \otimes \overline{q_h^t} \end{cases}, \tag{1}$$

In this notation, $\otimes$ denotes the quaternion multiplication, $\overline{q}$ denotes the quaternion conjugate and $X : \{1, 0, 0\}$ (left) and $Y : \{0, 1, 0\}$ (up) are oriented considering the global coordinate system of our scene. Position and orientation of foot, tibia and thigh during multiple gait cycles are depicted in Fig. 6.

E. Kinematic Model Adjustment

Once the positions and orientations of the leg joints have been estimated, it is still necessary to apply another procedure to ensure that the motion is consistent with the biomechanical behavior of the leg. This can be done with the adjustment of a kinematic leg model with biomechanical constraints. Thus, the leg model has 3 DoF for the hip and ankle joints and 1 DoF for the knee, with boundaries. These complex boundaries can be obtained if the rotations are modeled using the circumduction-swing-twist parametrization proposed in [8]. The modeling of these boundaries is based on a spherical parametrization of orientations, ignoring variations in the radius direction, as the body segment has a constant size. Only the other

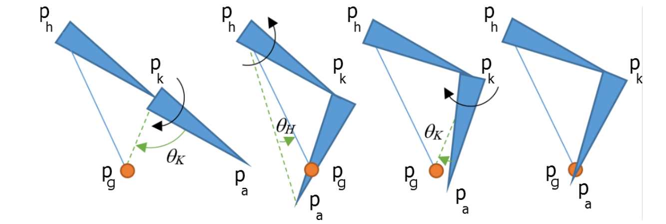

Fig. 7. A set of iterations of the CCD IK procedure applied to the leg, in order to make the ankle joint (P_a) match the measured goal (P_g).

two angles are considered; the circumduction angle θ, and swing amplitude or ψ, are considered. The range of θ goes from $-\pi$ to $+\pi$, and for each value there is a corresponding biomechanical limit of ψ. A set of n biomechanical limits are measured in the subject, such as the hips flexion, extension, abduction and adduction. Then, the rest are obtained by applying a cubic spline, with the first derivative at its starting and ending points ($\theta = -\pi$ and $\theta = \pi$, respectively) estimated as shown in Eq. 2, in order to get a smooth boundary over the entire circumduction movement.

$$\left.\frac{\partial \psi}{\partial \theta}\right|_1 = \left.\frac{\partial \psi}{\partial \theta}\right|_n = \frac{1}{2}\left(\frac{\psi_2 - \psi_1}{\theta_2 - \theta_1} + \frac{\psi_n - \psi_{n-1}}{\theta_n - \theta_{n-1}}\right). \tag{2}$$

The twist rotation needs a reference to which the current orientation is compared. This is obtained by considering the orientation of the parent joint as the neutral orientation of the current joint, and then rotating it with the θ and ψ values corresponding to the current orientation. This way the reference orientation differs from the current one only on the twist rotation. In order to fit the kinematic structure to the captured data, it is necessary to prioritize some of the captured features that are more trustworthy. In this case, we give more importance to the measured positions of the hip and ankle and to the orientation of the knee. These features are enough to adjust the kinematic model, as follows:

1) Initialize the pose, by setting the measured knee orientation to the hip and knee joints.
2) Place the hip joint at its measured position.
3) Apply the Cyclic Coordinate Descent (CCD) Inverse Kinematics (IK) procedure described in [9] to adjust the hip and knee orientations, so that the ankle joint matches its measured position.
4) Set the measured ankle orientation to the ankle joint.

The CCD IK procedure is fast and allows to check and correct the biomechanical configuration with respect to the modeled boundaries at each iteration, if required. Therefore, this additional procedure allows to satisfactorily infer the non-prioritized motion of the subject, preserving the biomechanical constraints. Fig. 7 shows how CCD works in the case of the leg, applied in the plane perpendicular to the knee joint rotation axis, with rotation angles and directions calculated at each iteration as shown in Eq. 2 and 3.

Considering a joint J situated at the position $p_J \in \mathbb{R}^3$, we apply our segment rotations by defining both the angles θ_J

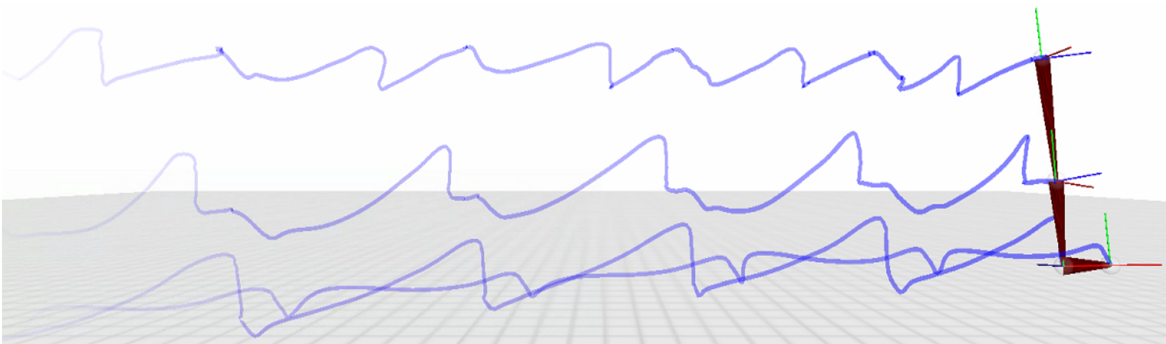

Fig. 6. Position and orientation of foot, tibia and thigh during multiple gait cycles.

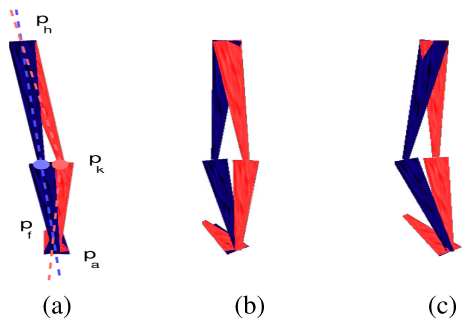

Fig. 8. 3D reconstructed leg before (left) and after applying the IK module (right) from (a)back view and (b),(c) side view are shown.

and the axis r_J as following,

$$\begin{cases} \theta_J = \frac{p_A - p_J}{||p_A - p_J||} \cdot \frac{p_G - p_J}{||p_G - p_J||} \\ r_J = \frac{p_A - p_J}{||p_A - p_J||} \times \frac{p_G - p_J}{||p_G - p_J||} \end{cases} . \tag{3}$$

An angle and it's corresponding axis (θ_J, r_J) can then define the quaternion q_J orienting the associated bone segment. The termination criteria of this process depends on the considered error between P_g and P_a, and the maximum number of iterations. As the leg is a simple multi-body mechanism it normally converges after a few iterations, in less than $1ms$. The obtained accuracy is higher in the hip and ankle joints, than in the knee, as the measured hip and ankle positions are explicitly considered in the adjustment. In the general case, according to the experiments done in [8], in a similar context but considering the whole body structure, the RMS accuracy error of CCD, per joint, when partial measurements are used is approximately of 0.03 for a displacement normalized by the height of the person. Finally, Fig. 8 shows the differences between the reconstructed leg with and without this additional procedure. It can be observed, especially in the knee joint, how applying this kinematic model adjustment helps to preserve the biomechanical characteristics of the legs motion.

IV. Conclusion

In this paper we have presented a low-cost computationally efficient method to accurately reconstruct the lower limbs. Our system uses body-worn inertial sensors on the thigh, tibia and foot and by utilising a customised gradient descent-based filter together with the local orientation of each sensor to estimate the associated body segment orientations and 3D positions. In addition, we distinguish between stance and swing phases to obtain drift-free linear velocity from accelerometer signals to calculate accurate 3D position of the foot during the entire gait cycle. Utilising the calculated foot position along with the estimated orientation of the thigh and tibia, 3D reconstruction of the entire leg was developed via a series of quaternion based geometrical transformations. Finally, it was shown that applying the customised kinematic model increased the accuracy of the system. It is envisaged that the proposed method can be used as a lightweight, low-cost system to monitor gait in real-time in non-constrained real-world environments.

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