Estimating Lower Limb Kinematics using
a Lie Group Constrained EKF and a Reduced Wearable IMU Count

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Abstract—This paper presents a novel algorithm using Lie group representation of position and orientation alongside a constrained extended Kalman filter (CEKF) to accurately estimate pelvis, thigh, and shank kinematics during walking using only three wearable inertial sensors. The algorithm iterates through the prediction update (kinematic equation), measurement update (pelvis height, zero velocity update, flat-floor assumption, and covariance limiter), and constraint update (formulation of hinged knee joints and ball-and-socket hip joints). The paper also describes a novel Lie group formulation of the assumptions implemented in the said measurement and constraint updates. Evaluation of the algorithm on nine healthy subjects who walked freely within a \(4 \times 4m^2\) room shows that the knee and hip joint angle root-mean-square errors (RMSEs) in the sagittal plane for free walking were \(10.5 \pm 2.8^\circ\) and \(9.7 \pm 3.3^\circ\), respectively, while the correlation coefficients (CCs) were \(0.89 \pm 0.06\) and \(0.78 \pm 0.09\), respectively. The evaluation demonstrates a promising application of Lie group representation to inertial motion capture under reduced-sensor-count configuration, improving the estimates (i.e., joint angle RMSEs and CCs) for dynamic motion, and enabling better convergence for our non-linear biomechanical constraints. To further improve performance, additional information relating the pelvis and ankle kinematics is needed.

I. INTRODUCTION

Human pose estimation involves tracking the pose (i.e., position and orientation) of body segments from which joint angles can be calculated. It finds application in robotics, virtual reality, animation, and healthcare (e.g., gait analysis). Traditionally, human pose is captured within a laboratory setting using optical motion capture (OMC) systems with up to millimeter position accuracy when properly configured and calibrated. However, recent miniaturization of inertial measurement units (IMUs) has paved the path toward inertial motion capture (IMC) systems suitable for prolonged use outside of the laboratory.

Commercial IMCs attach one sensor per body segment (OSPS) [1], which may be considered too cumbersome and expensive for routine daily use by a consumer due to the number of IMUs required. Each IMU typically tracks the orientation of the attached body segment using an orientation estimation algorithm (e.g., [2, 3]), which is then connected via linked kinematic chain, usually rooted at the pelvis. A reduced-sensor-count (RSC) configuration, where IMUs are placed on a subset of body segments, can improve user comfort, reduce setup time and system cost. However, utilizing fewer sensors inextricably reduces the kinematic information available which must be inferred by enforcing mechanical joint constraints or making dynamic balance assumptions. Developing a comfortable IMC for routine daily use may facilitate interactive rehabilitation [4, 5], and possibly the study of movement disorder progression to enable predictive diagnostics.

RSC performance depends on how the algorithm (i) tracks the body pose, and (ii) infers the kinematic information of these body segments lacking attached sensors. The algorithm may leverage our knowledge of human movement either through data obtained in the past (i.e., observed correlations between co-movement of different body segments) or by using a simplified model of the human body. Data-driven approaches (e.g., nearest-neighbor search [6] and bidirectional recurrent neural network [7]) are able to recreate realistic motion suitable for animation-related applications. However, these approaches are normally biased toward motions already contained in the database which may limit their use in monitoring pathological gait. Model-based approaches reconstruct body motion using kinematic and biomechanical models (e.g., constrained Kalman filter (KF) [8], extended KF [9], particle filter [10], and window-based optimization [11]). Within model-based approaches, using optimization-based estimators can be appealing due to its relative ease to setup and understand. However, it can be very inefficient in higher dimensions. When estimating the state across time, a recursive estimator can take advantage of the substructure and reduce the state dimension, making the estimator efficient and appropriate for online use [12].

Recent work on pose estimation has shown that using a Lie group to represent the states of recursive estimator is a promising approach. Such algorithms typically represent the body pose as a chain of linked segments using matrix Lie groups, specifically the special orthogonal group, \(SO(n)\), and special Euclidean group, \(SE(n)\), where \(n = 2, 3\), are the spatial dimensions of the problem. Traditionally, body poses have been represented using Euler angles or quaternions [9, 10]. Some early work in the field ([13] and [14]) investigated representations and propagation of pose uncertainty, the latter in the context of manipulator kinematics and the latter focused on \(SE(3)\). This was followed by the formulation of Lie group-based recursive estimators (e.g., extended KF (EKF) [15] and unscented KF (UKF) [16]). Recently, Lie group-based recursive estimators were used to solve the pose estimation problem. Cesic et al. estimated pose from marker measurements and achieved significant improvements compared to an Euler angle representation [17]; and even

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supplemented the approach with an observability analysis
[18]. Joukov et al. represented pose using $SO(n)$ with
measurements from IMUs under an OSPS configuration.
Results also improved, because the Lie group representation
is singularity free [19].

This paper describes a novel human pose estimator that
uses a Lie group representation, propagated iteratively using
a CEKF to estimate lower body kinematics for an RSC
configuration of IMUs. It builds on prior work [8] but
instead represents the state variables as Lie groups, specif-
ically $SE(3)$, to track both position and orientation (8)
only tracks position). Furthermore, this paper describes a
novel Lie group formulation for assumptions specific to pose
estimation, such as zero velocity update, and biomechanical
constraints (e.g., constant thigh length and a hinged knee
joint). Note that this algorithm is different from [19] in
that the state (i.e., body pose) was represented as $SE(3)$
instead of $SO(n)$. This representation allows for tracking of
the global position of the body, incorporating IMU measure-
ments in the prediction step, and a simpler implementation
of measurement assumptions at the cost of requiring an
additional constraint step. The design was motivated by
the need for a better state variable representation which
would potentially better model the biomechanical system to
infer the missing kinematic information from uninstrumented
body segments. The contributions of this paper advance the
development of gait assessment tools for comfortable and
long-term monitoring of lower body movement.

II. ALGORITHM DESCRIPTION

The proposed algorithm, $LGKF-3IMU$, uses a similar
model and assumptions to our prior work in [8], denoted
as $CKF-3IMU$, albeit expressed in Lie group representation,
to estimate the orientation of the pelvis, thighs, and shanks
with respect the world frame, $W$. using only three IMUs
attached at the sacrum and shanks, just above the ankles (Fig.
1). Using a Lie group representation enables the tracking
of not just position but also of orientation singularity free
(note that $CKF-3IMU$ only tracked position and assumed
orientation as perfect), whilst improving performance for
dynamic movements and utilizing fewer assumptions. Fig.
2 shows an overview of the proposed algorithm. $LGKF-
3IMU$ predicts the shank and pelvis positions through double
integration of their linear 3D acceleration (obtained after a
pre-processing step of IMU measurements). Orientation is
obtained from a third party orientation estimation algorithm.
Positional drift due to sensor noise that accumulates in the
double integration of acceleration was mitigated through the
following assumptions: (1) the ankle 3D velocity and
height above the floor are zeroed whenever a footstep is
detected; (2) the pelvis $z$ position is approximated as the
length of the unbent leg(s) above the floor. Furthermore,
to contain the ever-growing error covariance for the pelvis
and ankle positions, a pseudo-measurement equal to the
current pose estimate with a fixed covariance is made. Lastly,
biomechanical constraints enforce constant body segment
length; and a hinge knee joint (one degree of freedom (DOF))
with limited range of motion (ROM). The pre- and post-
processing parts remains exactly the same as the $CKF-3IMU$
algorithm.

Fig. 1. Model of the lower body used by LGKF-3IMU. The circles denote
joint positions, the solid lines denote instrumented body segments, whilst
the dashed lines denote segments without IMUs attached (i.e., thighs).

A. Lie group and Lie algebra

The matrix Lie group $G$ is a group of $n \times n$ matrices that
is also a smooth manifold (e.g., $SE(3)$). Group composition
and inversion (i.e., matrix multiplication and inversion) are
smooth operations. Lie algebra $\mathfrak{g}$ represents a tangent space
of a group at the identity element [20]. The elegance of Lie
theory lies in it being able to represent curved objects using
a vector space (e.g., Lie group $G$ represented by $\mathfrak{g}$) [21].

The matrix exponential $\exp_G : \mathfrak{g} \rightarrow G$ and matrix loga-
ithm $\log_G : G \rightarrow \mathfrak{g}$ establish a local diffeomorphism between
the Lie group $G$ and its Lie algebra $\mathfrak{g}$. The Lie algebra $\mathfrak{g}$ is
a $n \times n$ matrix that can be represented compactly with an
$n$ dimensional vector space. A linear isomorphism between
$\mathfrak{g}$ and $\mathbb{R}^n$ is given by $G : \mathfrak{g} \rightarrow \mathbb{R}^n$ and $ \mathfrak{g} : \mathbb{R}^n \rightarrow \mathfrak{g}$. An illustration of the said mappings are given in Fig. 3.
Furthermore, the adjoint operators of a Lie group, denoted as $Ad_G(X)$, and Lie algebra, denoted as $ad_G(X)$ will be
used in later sections. For a more detailed introduction to
Lie groups refer to [12, 21, 22].
B. System, measurement, and constraint models

The system and measurement models are presented below

\[
X_k = f(X_{k-1}, n_{k-1}) = X_{k-1} \exp_G([\Omega(X_{k-1})+n_{k-1}] G) \tag{1}
\]

\[
Z_k = h(X_k) \exp_G ([m_k]^G), \quad D_k = c(X_k) \tag{2}
\]

where \( k \) is the time step; \( X_k \in G \) is the system state, an element of state Lie group \( G \); \( \Omega(X_k) : G \to \mathbb{R}^p \) is a non-linear function; \( n_k \) is a zero-mean process noise vector with covariance matrix \( Q_k \) (i.e., \( n_k \sim \mathcal{N}_{\mathbb{R}^p} (0, Q_k) \)); \( Z_k \in G_1 \) is the system measurement, an element of measurement Lie group \( G_1 \); \( h(X_k) : G \to G_1 \) is the measurement function; \( m_k \) is a zero-mean measurement noise vector with covariance matrix \( R_k \) (i.e., \( m_k \sim \mathcal{N}_{\mathbb{R}^p} (0, R_k) \)); \( D_k \in G_2 \) is the constraint state, an element of constraint Lie group \( G_2 \); \( c(X_k) : G \to G_2 \) is the equality constraint function the state \( X_k \) must satisfy. Similar to [17, 23], the state distribution of \( X_k \) is assumed to be a concentrated Gaussian distribution on Lie groups (i.e., \( X_k = \mu_k \exp_G (\epsilon_k G) \) where \( \mu_k \) is the mean of \( X_k \) and Lie algebra error \( \epsilon \sim \mathcal{N}_{\mathbb{R}^p} (0, P) \) ) [13]. The Lie group state variables \( X_k \) model the position, orientation, and velocity of the three instrumented body segments (i.e., pelvis and shanks) as \( X_k = \text{diag} (T^p_k, T^{ت}_t, \nu^p_k, \nu^t_k) \in G = SE(3)^3 \times \mathbb{R}^9 \) where \( A^T B \in SE(3) \) denotes the pose of body segment \( B \) relative to frame \( A \), and \( \nu^x = [I_{3 \times 3} \quad \nu^x]^{T} \) is the trivial mapping of a 3D vector to an element in \( SE(3) \). If frame \( A \) is not specified, assume reference to the world frame, \( W. \) \( \text{exp} (\cdot) \), \( \text{log} (\cdot) \), and \( \text{Ad} (X_k) \) are constructed similarly. See [12] for \( SE(3) \) operator definitions.

C. Lie group constrained EKF (LG-CEKF)

The a priori, a posteriori, and constrained state for time step \( k \) are denoted by \( \hat{\mu}_k^+, \hat{\mu}_k^- \), and \( \hat{\mu}_k^\bullet \), respectively. The a priori and a posteriori error covariance matrices are denoted as \( P_k^+ \) and \( P_k^- \), respectively. The KF is based on the Lie group EKF, as defined in [23].

1) Prediction step: estimates the a priori state \( \hat{\mu}_k^+ \) at the next time step and may not necessarily respect the kinematic constraints of the body, so joints may become dislocated after this prediction step. The mean propagation of the three instrumented body segments is governed by Eq. (3) (where \( \hat{\Omega}_k^+ = \hat{\Omega}(\hat{\mu}_k^+) \) and \( \Omega(X_k) \) is the motion model for the three instrumented body segments. For the sake of brevity, only the motion model of the position, orientation, and velocity for body segment \( b \) is shown (Eqs. (4)). The measured acceleration and orientation of segment \( B \) are denoted as \( \hat{\nu}_k^B \) and \( \hat{R}_k^B \). The process noise for body segment \( b \) is shown in Eq. (5) where \( \sigma_{acc}^b \) and \( \sigma_{ori}^b \) denote the noise variances of the measured acceleration and orientation. Note that one may use the measured angular velocity to predict orientation. However, we chose setting angular velocity to zero to simplify computations related to position, knowing that the orientation will be updated in the measurement step using measurements from a third party orientation estimation algorithm, accounting for angular velocity.

\[
\hat{\nu}_k^B = \hat{\nu}_k^B \exp_G ([\hat{\Omega}_k^+]_G) \tag{3}
\]

\[
\Omega^B(X_k) = [(\Delta t \nu_k^B + \hat{\Omega}_k^+ \nu_k^B)_T]^T \tag{4}
\]

\[
\eta^B = [\Delta t \sigma_{acc}^b]^T [\sigma_{ori}^b]^T \Delta t (\delta_G)^T]^T \tag{5}
\]

The state error covariance matrix propagation is governed by Eq. (6) where \( F_k \) represents the matrix Lie group equivalent to the Jacobian of \( f(X_{k-1}, n_{k-1}) \). \( \mathcal{G}_{k} \) represents the linearization of the motion model, \( \mathcal{Q}_k \) is constructed from with diagonal values from \( \sigma_n^2 \), and \( \mathcal{M}_k = \mu_k \mathcal{G}_k \exp_G (\epsilon_k G) \) represents the state with infinitesimal perturbation \( \epsilon \). Refer to the supplementary material [24] for the explicit definition of the motion model, \( \mathcal{Q}_k (X_k) \), and \( \mathcal{G}_k \).

\[
P_{k+1} = F_k P_k^+ F_k^T + \mathcal{Q}_k \mathcal{Q}_k^T \tag{6}
\]

\[
F_k = \text{Ad}_G (\exp_G (\hat{\Omega}_k^+) G) \tag{7}
\]

\[
\mathcal{G}_k = \frac{\partial}{\partial \epsilon} \hat{\Omega}(\epsilon) |_{\epsilon=0} \tag{8}
\]

\[
\mathcal{Q}_k (X_k) = \sum_{i=0}^{\infty} [\frac{(-1)^i}{(i+1)!}] \text{ad}_G (X_k)^i \tag{9}
\]

2) Measurement update: estimates the state at the next time step by: (i) updating the orientation state using new orientation measurements of body segments; (ii) encouraging pelvis \( z \) position to be close to initial standing height \( z_p \), and by; (iii) enforcing ankle velocity to reach zero, and the ankle \( z \) position near the floor level, \( z_f \). The a posteriori state \( \hat{\mu}_k^\bullet \) is calculated following the Lie EKF equations below. \( \mathcal{H}_k \) can be seen as the matrix Lie group equivalent to the Jacobian of \( h(X_k) \); and is defined as the concatenation of \( \mathcal{H}_{ori} \) and \( \mathcal{H}_{mp} \). \( \mathcal{H}_{ori} \) and/or \( \mathcal{H}_{mp} \) are also concatenated to \( \mathcal{H}_k \) when the left and/or right foot contact is detected (See [8, Eq. (9)]). Each component matrix will be described later. \( Z_k, h(X_k), \) and \( R_k \) are constructed similarly to \( \mathcal{H}_k \) but combined using \( \text{diag} \) instead of concatenation (e.g., \( R_k = \text{diag}(\sigma_{ori}, \sigma_{mp}) \) )

\[
K_k = P_k^+ \mathcal{H}_k^T (\mathcal{H}_k P_k^+ \mathcal{H}_k^T + R_k)^{-1} \tag{10}
\]

\[
\nu_k = K_k ([\text{log}_{G_1} (h(\hat{\mu}_k^-) \mathcal{G}_k)]^G) \tag{11}
\]

\[
\hat{\mu}_k^\bullet = \hat{\mu}_k^- \exp_G ([\nu_k]^G) \tag{12}
\]

\[
\mathcal{H}_k = \frac{\partial}{\partial \epsilon} [\text{log}_{G_1} (h(\hat{\mu}_k^-) \mathcal{G}_k)] |_{\epsilon=0} \tag{13}
\]

The measurement functions of the (i) orientation update, (ii) pelvis height assumption, and (iii) ankle velocity and flat floor assumptions are defined by Eqs. (14)-(17) with measurement noise variances \( \sigma_{ori}^2 (9 \times 1 \text{ vector}) \), \( \sigma_{mp}^2 (1 \times 1 \text{ vector}) \), and \( \sigma_{z_f}^2 (4 \times 1 \text{ vector}) \), respectively. \( \mathbf{I}_{ij} \) and \( 0_{ij} \) denote \( i \times j \) identity and zero matrices; \( \mathbf{I}_{z_1}, \mathbf{I}_{z_2}, \mathbf{I}_{z_3} \), and \( \mathbf{I}_{z_0} \) denote 4 \( \times \) vectors whose \( 1^{\text{st}} \) to \( 4^{\text{th}} \) row, respectively, are 1, while the rest are 0; and the \( \circ \) operator is as defined in [12, Eq. (72)], \( \mathcal{H}_{ori} \), \( \mathcal{H}_{mp} \), and \( \mathcal{H}_{z} \) (Eqs. (18)-(20)) are calculated by applying Eq. (13) to their corresponding measurement function, followed by tedious algebraic manipulation and first
order linearization (i.e., \( \exp([\epsilon]') \approx \mathbf{I} + [\epsilon]' \)). See details in the supplementary material [24].

\[
h_{ori}(\mathbf{X}_k) = \text{diag}(\mathbf{R}_k^w, \mathbf{R}_k^l, \mathbf{R}_k^s)
\]

\[
\mathbf{Z}_{ori} = \text{diag}(\tilde{\mathbf{R}}_k^w, \tilde{\mathbf{R}}_k^l, \tilde{\mathbf{R}}_k^s)
\]

\[
h_{mp}(\mathbf{X}_k) = \mathbf{I}_T^z \mathbf{T}^{\mathbf{p}i}_{\mathbf{i}o}, \quad \mathbf{Z}_{mp} = z_p
\]

\[
h_{ls}(\mathbf{X}_k) = \begin{bmatrix} \mathbf{v}^z \\
\mathbf{I}_T^z \mathbf{T}^{\mathbf{ls}i}_{\mathbf{i}o} \end{bmatrix}, \quad \mathbf{Z}_{ls} = \begin{bmatrix} 0_{3 \times 1} \\
0_{3 \times 1} \\
0_{3 \times 3} \mathbf{I}_{3 \times 3} \end{bmatrix}
\]

\[
\mathcal{H}_{ori} = \begin{bmatrix} 0_{3 \times 3} \mathbf{I}_{3 \times 3} \\
0_{3 \times 3} \mathbf{I}_{3 \times 3} \\
0_{3 \times 3} \mathbf{I}_{3 \times 3} \\
0_{9 \times 9} \end{bmatrix}
\]

\[
\mathcal{H}_{mp} = \begin{bmatrix} \mathbf{I}_T^z \mathbf{P}^h \mathbf{p}^h & 0_{1 \times 6} & 0_{1 \times 6} & 0_{1 \times 9} \end{bmatrix}
\]

\[
\mathcal{H}_{ls} = \begin{bmatrix} \mathbf{I}_T^z \mathbf{P}^h \mathbf{p}^h & 0_{1 \times 6} & 0_{1 \times 6} & 0_{1 \times 9} \end{bmatrix}
\]

Lastly, the error covariance must be prevented from growing indefinitely and becoming badly conditioned, as will occur naturally when tracking global position of objects without any global position reference. At this step, a pseudo-measurement equal to the current state \( \tilde{\mathbf{p}}_k^z \) is used (implemented by \( \mathcal{H}_{lim} = \begin{bmatrix} 1_{18 \times 18} & 0_{18 \times 9} \end{bmatrix} \)) with some measurement noise of variance \( \sigma_{lim}^2 \) (9 \times 1 vector). The covariance \( \mathbf{P}_k^z \) is then calculated through Eqs. (21)-(23).

\[
\mathcal{H}_k^T \mathbf{H}_k + \mathbf{R}_k = \text{diag}(\mathbf{P}_k^z)^T \text{diag}(\mathbf{P}_k^z) \mathbf{R}_k
\]

\[
\mathbf{K}_k = \mathbf{P}_k^z \mathbf{H}_k^T \mathbf{H}_k + \mathbf{R}_k
\]

\[
\mathbf{P}_k = \mathbf{K}_k \mathbf{P}_k \mathbf{H}_k^T \mathbf{P}_k + \mathbf{R}_k
\]

3) Satisfying biomechanical constraints: After the preceding updates, the joint positions or angles may be beyond their allowed range. The constraint update corrects the kinematic state estimates to satisfy the biomechanical constraints of the human body by projecting the current a posteriori state \( \tilde{\mathbf{p}}_k^z \) estimate onto the constraint surface, guided by our uncertainty in each state variable, encoded by \( \mathbf{P}_k^z \). The following biomechanical constraint equations are enforced: (i) estimated thigh vector lengths (\( ||v^z|| \) and \( ||\tau^z|| \)) equal the thigh lengths \( d^z \) and \( d^z; \) (ii) both knees act as hinge joints (formulation similar to [10, Sec. 2.3 Eqs. (4)]); and (iii) the knee joint angle is within realistic ROM. The constrained state \( \tilde{\mathbf{p}}_k^z \) can be calculated using the equations below, similar to the measurement update of [23] with zero noise where \( \mathbf{C}_k = \begin{bmatrix} \mathbf{C}_{l,k} & \mathbf{C}_{l,k} \end{bmatrix} \). \( \mathbf{C}_{l,k} \) is the concatenation of \( \mathbf{C}_{l,k}, \mathbf{C}_{l,k} \), and \( \mathbf{C}_{l,k} \), the last matrix is produced when the knee angle, \( \alpha_k \), is bounded (i.e., \( \alpha_{k,min} \leq \alpha_k \leq \alpha_{k,max} \)). Each component matrix will be described later. \( \mathbf{C}_{l,k} \) can be derived similarly, while \( \mathbf{D}_k \) and \( \mathbf{C}(\mathbf{X}_k) \) are constructed similarly to \( \mathbf{Z}_k \).

\[
\mathbf{K}_k = \mathbf{P}_k^z \mathbf{C}_k^T \left( \mathbf{C}_k \mathbf{P}_k^z \mathbf{C}_k^T \right)^{-1}
\]

\[
\mathbf{\nu}_k = \mathbf{K}_k \left[ \log_{\mathbf{G}} \left( c \left( \tilde{\mathbf{p}}_k^z \right)^{-1} \mathbf{D}_k \right) \right]_{G_k}
\]

\[
\tilde{\mathbf{p}}_k^z = \tilde{\mathbf{p}}_k^z \exp_{\mathbf{G}} \left( \mathbf{\nu}_k \right)
\]

\[
\mathbf{C}_k = \frac{d}{d\epsilon} \log_{\mathbf{G}} \left( c \left( \tilde{\mathbf{p}}_k^z \right)^{-1} c \left( \mathbf{\mu}_k^z \right) \right)_{G_k} \bigg| \epsilon = 0
\]

The constraint functions are similar to [8, Sec. II-E.3] but expressed under \( SE(3) \) state variables. Firstly, the thigh length constraint is shown in Eq. (30) where \( \tau^z \left( \tilde{\mathbf{p}}_k^z \right) \) denotes the thigh vector. Secondly, the hinge knee joint constraint is defined by Eq. (31). Thirdly, the knee ROM constraint is defined by Eq. (34) and is only enforced if the knee angle, \( \alpha_k \), is outside the allowed ROM. The bounded knee angle, \( \alpha_k \), is calculated by Eqs. (32) and (33). Lastly, \( \mathbf{C}_{l,k} \), \( \mathbf{C}_{l,k} \), and \( \mathbf{C}_{l,k} \) are calculated by applying Eq. (27) to their corresponding constraint functions, similar to \( \mathcal{H}_{mp} \). Refer to the supplementary material for full derivation [24].

\[
\mathbf{E} = \begin{bmatrix} 0 & 0 & 1 \\
0 & \mathbf{T}^{\mathbf{p}i}_{\mathbf{i}o} & 0 \end{bmatrix} \mathbf{p}^h
\]

\[
\mathbf{r}^z \left( \tilde{\mathbf{p}}_k^z \right) = \mathbf{r}^z \left( \tilde{\mathbf{p}}_k^z \right)^T \mathbf{r}^z \left( \tilde{\mathbf{p}}_k^z \right) - (d^z)^2 = 0
\]

\[
\alpha_k = \min \left( \alpha_k, \frac{\pi}{2} \right) \frac{\pi}{2}
\]

\[
\mathbf{c}_{\mathbf{k}} \left( \mathbf{p}^h \right) = \left( \mathbf{r}^z \left( \mathbf{p}^h \right)^T \mathbf{r}^z \left( \mathbf{p}^h \right) \sin (\alpha_k) \right) 
\]

III. Experiment

The dataset from [8] was used to evaluate LGKF-3IMU. It involved movements listed in Table I from nine healthy subjects (7 men and 2 women, weight 63.0 ± 6.8 kg, height 1.70 ± 0.06 m, age 24.6 ± 3.9 years old), with no known gait abnormalities. Raw data were captured using a commercial IMC (i.e., Xsens Awinda) with IMUs attached to the pelvis and ankles, compared against a benchmark OMC (i.e., Vicon Plug-in Gait) within an ~4 x 4 m² capture area.

| Types of Movements Done in the Validation Experiment | Description | Duration | Group |
|-----------------------------------------------------|-------------|----------|-------|
| Walk straight and return | ~30 s | F |
| Figure-of-eight Walk along figure-of-eight path | ~60 s | F |
| Zig-zag Walk along zig-zag path | ~60 s | F |
| 5-minute walk Unscripted walk and stand | ~300 s | F |
| Speedskater | ~30 s | D |
| Jog | ~30 s | D |
| Jumping jacks | ~30 s | D |
| High knee jog | ~30 s | D |

F denotes free walk, D denotes dynamic.

The variance parameters used to generate the process and measurement error covariance matrix Q and R are shown in Table II.

| Parameters for Covariance Matrices, Q and R. | Q | R |
|-----------------------------------------------|----------------|----------------|
| \( \sigma_{\mathbf{a}} \) (m²s⁻²) | 10² | 10⁻² |
| \( \sigma_{\mathbf{b}} \) (m²s⁻²) | 10⁻² | 0.1 |
| \( \sigma_{\mathbf{c}} \) (m²s⁻²) | 0.011 | 0.01 |
| \( \sigma_{\mathbf{d}} \) (m²s⁻²) | 0.001 | 0.01 |

Where \( \mathbf{1}_n \) is an \( n \times n \) row vector with all elements equal to 1.
Lastly, the evaluation was done using the following metrics: (1) joint angles RMSE with bias removed and coefficient of correlation (CC) of the hip in the Y, X, and Z planes and of the knee in the Y plane; and (2) Total travelled distance (TTD) deviation (i.e., TTD error with respect to the actual TTD) of the ankles. Refer to [8, Sec. III] for more details.

IV. RESULTS

Fig. 4 shows the knee and hip joint angle RMSE (bias removed) and CC compared against the OMC output. Y, X, and Z refers to the sagittal, frontal, and transverse planes, respectively. Fig. 5 shows a sample Walk trial. Table III shows the TTD deviation at the ankles for free walk and jogging. Refer to [25] for videos of sample trials.

![Fig. 4. The CC of knee (Y) and hip (Y, X, Z) joint angles for LGKF-3IMU (prefix LG) and CKF-3IMU (prefix C) at each motion type.](image)

![Fig. 5. Knee (Y) and hip (Y, X, Z) joint angle output of LGKF-3IMU (left) and CKF-3IMU (right) in comparison with the benchmark system (Vicon) for a Walk trial. The subject walked straight from \( t = 0 \) to \( 3 \) s, turned \( 180^\circ \) around from \( t = 3 \) to \( 5.5 \) s, and walked straight to the original starting point from \( 5.5 \) s until the end.](image)

TABLE III

| Joint Angle RMSE (°) | knee sagittal | hip sagittal | hip frontal | hip transverse |
|---------------------|--------------|-------------|-------------|---------------|
| CKF-3IMU biased     | 11.1 ± 2.9   | 11.8 ± 3.2  | 7.5 ± 3.1   | 17.5 ± 4.7    |
| mean                | -1.2 ± 4.2   | -4.3 ± 4.4  | -2.2 ± 4.2  | -4.0 ± 9.7    |
| no bias             | 10.0 ± 2.8   | 9.9 ± 3.1   | 6.1 ± 1.8   | 13.9 ± 2.4    |
| LGKF-3IMU biased    | 13.9 ± 4.5   | 11.6 ± 4.1  | 8.9 ± 4.2   | 17.0 ± 4.4    |
| mean                | 8.1 ± 4.8    | 4.6 ± 4.3   | -4.0 ± 5.3  | -3.3 ± 9.0    |
| no bias             | 10.5 ± 2.8   | 9.7 ± 3.3   | 6.4 ± 2.1   | 13.7 ± 2.4    |
| OPS biased          | 7.9 ± 3.2    | 12.4 ± 6.0  | 6.2 ± 2.6   | 19.8 ± 6.6    |
| mean                | 0.2 ± 6.1    | -10.9 ± 7.4 | 0.2 ± 2.5   | 8.8 ± 8.8     |
| no bias             | 5.0 ± 1.7    | 3.6 ± 1.7   | 4.1 ± 2.2   | 11.9 ± 4.3    |
| Cloete et al. [26]  | 11.5 ± 0.3   | 16.9 ± 3.6  | 9.0 ± 5.1   | 16.0 ± 8.8    |
| biased              | 8.5 ± 5.0    | 5.8 ± 3.8   | 7.3 ± 5.2   | 7.9 ± 4.9     |
| no bias             | 8.0 ± 5.0    | 5.8 ± 3.8   | 7.3 ± 5.2   | 7.9 ± 4.9     |

TABLE IV

| Joint Angle CC | knee sagittal | hip sagittal | hip frontal | hip transverse |
|---------------|--------------|-------------|-------------|---------------|
| CKF-3IMU      | 0.87 ± 0.08  | 0.74 ± 0.11 | 0.64 ± 0.12 | 0.33 ± 0.12   |
| LGKF-3IMU     | 0.89 ± 0.06  | 0.78 ± 0.09 | 0.63 ± 0.12 | 0.38 ± 0.12   |
| OPS           | 0.97 ± 0.03  | 0.95 ± 0.06 | 0.72 ± 0.19 | 0.28 ± 0.20   |
| Cloete et al. [26] | 0.89 ± 0.15  | 0.94 ± 0.08 | 0.55 ± 0.40 | 0.54 ± 0.20   |

Comparing processing times, LG-CEKF was slower than CKF but can still be used in real time; specifically, LG-CEKF and CKF processed a 1,000-frame sequence in ~2 and ~0.7 seconds, respectively, on an Intel Core i5-6500 3.2 GHz CPU [8], while the algorithm in [11] took 7.5 minutes on a quad-core Intel Core i7 3.5 GHz CPU. All set-ups used single-core non-optimized Matlab code.

Table III shows that despite successful reconstruction of relative pose, LGKF-3IMU had worse TTD for free walking than CKF-3IMU. It can also be observed from the sample video trial that the LGKF-3IMU had less displacement during the turn around (i.e., high rotational change).

V. DISCUSSION

Fig. 4 shows that although there was minimal hip and knee joint angle RMSE and CC improvement for free walk between CKF-3IMU and LGKF-3IMU, there was $2 - 15^\circ$ RMSE and 0.1 – 0.6 CC improvement among the dynamic movements (e.g., speedskater, jog, and high knee jog) indicating that the Lie group representation has indeed made the pose estimator capable of tracking more ADLs and not just walking. This result also agrees with [19]. Similar to IMC based systems, LGKF-3IMU also follows the trend of having sagittal (Y axis) joint angles similar to that captured by OMC systems (0.89 knee Y and 0.78 hip Y CCs), but with significant difference in frontal and transverse (X and Z axis) joint angles [8, 26]. Similar qualitative observations can be seen in Fig. 5, specifically, there were larger angle change for hip X ($t = 0$ to $3$ s and $t = 6$ to $8$ s) and hip Z ($t = 3$ to $5$ s). The sources of joint angle error are expected to be comprised of (i) model and (ii) sensor measurement errors. As the knee is not a perfect hinge joint, model error is expected, the extent of which will be further investigated in future work.

The knee and hip joint angle RMSEs and CCSs of CKF-3IMU, LGKF-3IMU, OPS, and related literature for free walking are shown in Table IV [8, 26]. The unbiased RMSEs of LGKF-3IMU, OPS, and Cloete’s show that utilizing fewer sensors does reduce accuracy ($2 - 5^\circ$) [26]. Despite LGKF-3IMU achieving ~0.89 joint angle CCs in the sagittal plane, the unbiased joint angle RMSE ($> 5^\circ$) makes its utility in clinical applications uncertain [27].
LGKF-3IMU was able to achieve comparable and occasionally better results (~0−0.6 CC improvement) than CKF-3IMU using fewer assumptions (i.e., encourage pelvis x and y position to approach the average of the left and right ankle x and y positions during the measurement update, and the prevention of knee angle decrease during the constraint update [8, Sec. II-E.2 and 3]); and only at one iteration (CKF-3IMU used an iterative projection scheme called smoothly constrained KF), indicating the robustness brought by the Lie group representation. Furthermore, LGKF-3IMU does not assume perfect orientation during the constraint update, in contrast to CKF-3IMU, which can be beneficial if new sensor information that informs segment orientation is added.

Limitations and Future Work

During longer-term tracking of ADLs, LGKF-3IMU, like [8], is unable to handle the activities of sitting or climbing stairs due to the pelvis height and/or flat floor assumptions; and is unable to track people with varus or valgus deformity, or those capable of hyperextending the knee due to the algorithm’s hinge knee joint and ROM constraints. Furthermore, it will share the limitations of the third-party orientation estimation and step detection algorithm used. Nevertheless, enabling longer-term tracking of ADL in the subject’s natural environment may lead to novel investigations of movement disorder progression and the identification of early intervention opportunities. Hence, developing solutions to further increase accuracy and overcome the said limitations (e.g., measuring inter-sensor distance [28], or leveraging long-term recordings and gait patterns) will be the focus of future work.

VI. Conclusion

This paper presented a Lie group CEKF-based algorithm (LGKF-3IMU) to estimate lower limb kinematics using a reduced sensor count configuration. The knee and hip joint angle RMSEs in the sagittal plane for free walking were 10.5 ± 2.8° and 9.7 ± 3.3°, respectively, while the CCs were 0.89 ± 0.06 and 0.78 ± 0.09, respectively. We also showed that LGKF-3IMU improves estimates for dynamic motion, and enables better convergence for our non-linear biomechanical constraints. To further improve performance, additional information relating the pelvis and ankle kinematics is needed (e.g., utilize sensors that give pelvis distance or position relative to the ankle). The source code for the LG-CEKF algorithm, supplementary material, and links to sample videos will be made available at [29].

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