A generic approach to inertial tracking of arbitrary kinematic chains

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ABSTRACT

Inertial tracking is still an area of active research, especially in the context of real-time human motion capture. Existing systems either propose loosely coupled tracking approaches, taking the resulting drawbacks into account, or they propose tightly coupled solutions limited to a fixed chain with few segments, but without any flexibility in changing the skeleton structure. Therefore, this paper proposes a generic approach for tracking arbitrary kinematic chains in a tightly coupled recursive filtering framework. The generic property as well as the tracking stability of the proposed system are demonstrated and initial experimental results concerning its accuracy are also presented.

Categories and Subject Descriptors

I.2.9 [**Robotics**]: Kinematics and dynamics; I.6.5 [**Simulation and Modeling**]: Model Development

General Terms

Theory, Algorithms

Keywords

Inertial motion capture, sensor fusion, body sensor network

1. INTRODUCTION

Many approaches to inertial tracking of kinematic chains arose in the past years. In particular for human motion tracking, a wide range of applications such as robot control [5], health assessment [9] and activity recognition [8] have been developed.

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Inertial motion capture is based on body sensor networks, where an IMU is attached to each major segment that should be tracked. These IMUs typically provide 3D linear acceleration, rotation speed and magnetic field measurements, from which orientation with respect to a global reference frame (usually aligned with gravity and local magnetic north) can be derived. Combining the local orientation estimates from individual IMUs with knowledge about their positioning on the body provides already a coarse posture tracking of a skeleton [11, 12, 13]. However, this decoupled estimation (loosely coupled approach) has numerous drawbacks: Joint constraints, such as those found in the human anatomy, cannot be included easily into the tracking; the correlations between the segments are lost during estimation; and high accelerations, especially appearing in lower limb segments during motion, result in errors, since orientation estimation requires distinguishing acceleration due to gravity from the overall measured acceleration [10]. Furthermore, tightly coupled systems, where all parameters and measurements are considered jointly in one estimation problem, have previously been shown to provide better performance [7].

Therefore, previous work in human motion capture has already started to explicitly model kinematic chains to some extend, e.g. [10] propagates linear accelerations through the segment hierarchy to improve the identification of the gravity components under high acceleration motions, however, they still decouple the orientation estimation of each segment. The authors in [1] propose a semi-coupled approach, where chains up to two segments are jointly handled in one filter during estimation. More specifically, arms consisting of upper and forearm segments, or shoulder and elbow joints, are handled in one filter, which is then loosely coupled to another filter estimating the torso orientation. The authors in [4] propose a similar system, however, their approach considers only one limb. In summary, a generic approach to easily model and track arbitrary kinematic chains is missing.

Recently, kinematic chains have been expressed using the Denavit-Hartenberg (DH) representation [2, 3, 4]. This is widely used in robotics and provides easy forward and inverse kinematics. Also, for recursive filtering, this representation has some advantages over the frequently used quaternions [12]: joints with varying DoFs can be modeled easily; estimation parameters and noises are associated to real anatomical rotation axes and are thus intuitively interpreted and in contrast to e.g. [1], which uses a mix of quaternions and Euler angles, the full chain can be modeled uniformly.

As a conclusion from the above state-of-the-art, this paper contributes a generic formulation and framework for the tracking problem, consequently modeling the hierarchical nature of arbitrary kinematic chains based on DH parameters. After introducing the mathematical basis in Section 2, a state-space model is developed in Section 3, which can be used with any recursive filtering algorithm. The proposed framework allows for an easy setup and tracking of arbitrary kinematic chains, also under fast motions, as will be shown through several proof-of-concept experiments in Section 4. The paper closes with a conclusion and an outline of future work in Section 5.

2. RECURSIVE CHAIN FORMULATION

A set of Denavit-Hartenberg parameters is a tuple of the four parameters θ (rotation around z-axis), d (translation on z-axis), a (translation on x-axis) and α (rotation around x-axis). From these parameters a homogeneous transformation can be generated:

$$DH(\theta, d, a, \alpha) = \begin{pmatrix} \cos\theta & -\sin\theta\cos\alpha & \sin\theta\sin\alpha & a\cos\theta \\ \sin\theta & \cos\theta\cos\alpha & -\cos\theta\sin\alpha & a\sin\theta \\ 0 & \sin\alpha & \cos\alpha & d \\ 0 & 0 & 0 & 1 \end{pmatrix}. \quad (1)$$

The upper left 3x3 matrix represents a rotation and can be extracted using the $rot(\cdot)$ operator. The translation is contained in the last column and can be accessed using $trans(\cdot)$. Only one DoF per transformation is allowed and only d or θ may be variable. In particular, for posture tracking, at current state, only θ is assumed time-dependent.

A kinematic path is a set of consecutively applied transformations:

$$DH_{path}(\{\theta, d, a, \alpha\}) := \prod_{i=0}^{n-1} H_i = \prod_{i=0}^{n-1} DH(a_i, d_i, \alpha_i, \theta_i). \quad (2)$$

A kinematic chain is an n-tree of DH transformations. IMUs attached to the segments are represented as leaves with fixed (calibrated) homogeneous transformations $\{H_{SI}\}$. Here, S denotes the frame of the segment the IMU is attached to and I denotes the IMU frame. While IMUs provide their measurements relative to a global (earth) frame G, the chain root is typically defined in a (local) world coordinate system or visualization frame, here denoted W. Hence, H_{GW} describes the transformation between these reference frames and is also considered a calibration parameter.

The above definitions allow an IMU path, i.e. the transformation from the global frame to an IMU frame, to be formulated as:

$$H_{GI} = H_{GW} \left[\prod_{i=0}^{n-1} DH(a_i, d_i, \alpha_i, \theta_i) \right] H_{SI}. \quad (3)$$

In order to derive a dynamic model for tracking and relate the time-dependent DH parameters to the IMU measurements, (3) needs to be derived with respect to time. Since the calibration parameters are assumed fixed, only

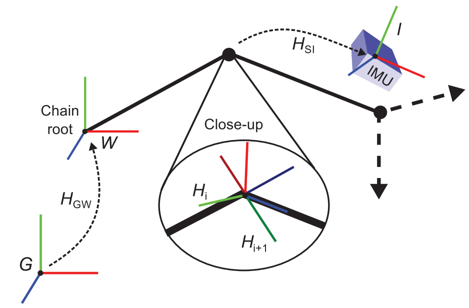

Figure 1: Kinematic chain structure. The close-up shows local coordinate frames which define the DoFs for this joint.

the derivatives of the chain transformations need to be computed. Taking advantage of the associative property, the first order derivative of a DH_{path} can found recursively:

$$\begin{aligned} DH_{path}(\{\theta, d, a, \alpha\})' &= (H_0 \cdots H_n)' = (H_0(H_1 \cdots H_n))' \\ &= H_0'(H_1 \cdots H_n) + H_0(H_1 \cdots H_n)', \end{aligned} \quad (4a)$$

where H_i is defined in (2) and the derivative can be computed using the chain rule. Analogously, the second order derivative is:

$$\begin{aligned} DH_{path}(\{\theta, d, a, \alpha\})'' &= (H_0'(H_1 \cdots H_n) + H_0(H_1 \cdots H_n)')' \\ &= H_0''(H_1 \cdots H_n) + 2H_0'(H_1 \cdots H_n)' + H_0(H_1 \cdots H_n)''. \end{aligned} \quad (4b)$$

An iterative formulation is also possible for more efficient computation.

3. RECURSIVE FILTERING

In order to use the above formulation in a recursive filtering framework, a state-space model, comprising state, dynamic and measurement models needs to be derived.

3.1 State and dynamic model

The state contains all time-dependent parameters of the kinematic chain, i.e. at current state the angles θ. These are obtained by vectorizing the chain using depth first traversal. In order to be able to track agile motions and correctly model the measured linear accelerations (as will be described below), constant angular acceleration is assumed between sample times. Hence, the state is:

$$x_t = \left(\{\theta_i, \dot{\theta}_i, \ddot{\theta}_i\}_{i=0}^{n-1} \right)^T \quad (5)$$

and the dynamic model is a standard constant angular acceleration model with white noise in acceleration (e.g. [1]).

3.2 Measurement models

In the following, the different IMU measurements are related to the state. The focus is on the inertial measurements, while the magnetometer model has been adapted from [1]. The terms, e, denote zero-mean Gaussian measurement noise.

3.2.1 Angular velocity

In order to relate the gyroscope measurements, y^ω, to the state, we start from the well-known kinematic equation [6]:

$$S\left(\omega_I^{GI}\right) = R_{GI}^T \dot{R}_{GI}, \tag{6}$$

where $S(\cdot)$ denotes the skew-symmetric matrix of a vector and $S^{-1}(\cdot)$ reverses this operation on a given matrix.

For an IMU attached to the k^{th} joint, the right side terms are then:

$$R_{GI,k} = rot\left[\left(\prod_{i=0}^{k-1} H_i\right) H_{SI,k}\right] \tag{7a}$$

$$\dot{R}_{GI,k} = rot\left[\left(\prod_{i=0}^{k-1} H_i\right)' H_{SI,k}\right], \tag{7b}$$

where the derivative on the right side is given in (4a). The final measurement equation is:

$$y^\omega = S^{-1}(R_{GI}^T \dot{R}_{GI}) + e^\omega \tag{8}$$

3.2.2 Acceleration

The linear acceleration, y^a, measured by an IMU at point t is composed of the acceleration due to gravity, g, and the body acceleration, $\ddot{t}$, in this point. Assuming a kinematic chain, the latter depends on the angular kinematics (in the state), the IMU position with respect to the adjacent segment and the segment lengths. The measurement equation for the k^{th} segment is:

$$y^a = R_{GI}^T\left(\ddot{t}_{GI} - g_G\right) + e^a, \tag{9}$$

with

$$\ddot{t}_{GI} = trans\left[\left(\prod_{i=0}^{k-1} H_i\right)'' H_{SI}\right]. \tag{10}$$

Here, the second derivative on the right side is given in (4b).

4. EXPERIMENTS

The proposed approach was implemented in C++ using an extended Kalman filter (EKF) as estimation tool. The experimentally tuned noise settings were kept equal for all experiments (with $v^\theta = I_3 \cdot 0.01$, $e^\omega = I_3 \cdot 0.002$ and $e^a = I_3 \cdot 0.01$). For calibrating the sensor positions with respect to the body, the method in [1] was adapted to generic kinematic chains and the required distances (IMU positions, segment lengths) were either measured or based on anthropometric tables. For brevity, the full chain definitions in terms of DH parameters are omitted here.

Five Trivisio[1] ColibriWireless IMUs, providing data at 100 Hz, were fixed to the body in different configurations using velcro straps.

To demonstrate the generic property and stability of the tracking approach, a video has been created, which shows real-time tracking (at IMU rate on an Intel Xeon, 2.67 GHz) of a complex kinematic chain. Starting from just a torso tracked with one IMU, additional segments and IMUs are gradually added until, eventually, a chain with five segments (including torso, shoulder, arm and a handled object) is tracked stably, even under high accelerations (see Figure 2). The video can be found at `http://youtu.be/_vGwfjuS9CU`.

[1]http://www.trivisio.com/

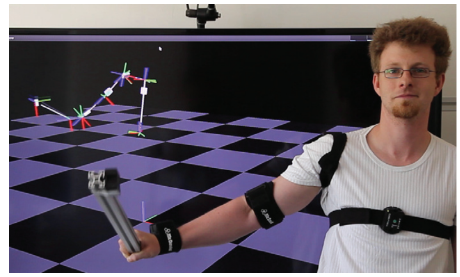

Figure 2: Real-time tracking of a kinematic chain with five segments, including a handled bar.

Figure 3: Two setups used for evaluating the tracking precision: upper body (left) and full arm (right). The red arrows mark the IMU positions.

In a second experiment, the tracking accuracy was qualitatively evaluated based on two frequently used setups as illustrated in Figure 3. For this, a person equipped with the sensor network was asked to draw certain shapes on a whiteboard, while keeping the pen rigidly with respect to the closest tracked segment. The drawings were then compared to the trajectory of the end effector, i.e. the wrist or hand respectively, as computed from the estimated joint angles and assumed segment lengths. Note that this experiment is particularly challenging, since it does not only evaluate joint angles, as is commonly done, but actual positions.

4.1 Upper body

The first setup is a commonly used upper body model (e.g. [8], cf. Figure 3 (left)). In this configuration, all IMUs attached to the arms affect the estimation of the torso pose. The subject was asked to simultaneously draw two squares on the whiteboard using the left and the right arm.

The results as presented in Figure 4 clearly show similar shapes, though fine features along the edges are not visible. For quantizing the precision, given that the whiteboard is planar, a plane was fitted into the estimated trajectories and the average distance to the plane was computed with 0.13 cm. This is already a promising result, given the various error sources in this experiment, such as unmodeled torso translations, hand movements and the offset of the wrist with respect to the whiteboard, as well as, the seg-

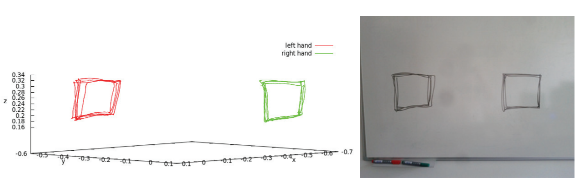

Figure 4: Upper body setup: estimated wrist trajectory (left) compared to the actual drawing (right).

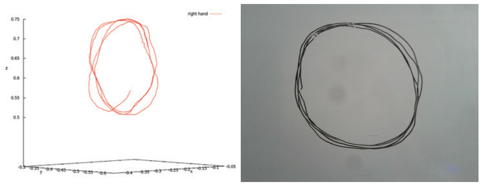

Figure 5: Full arm setup: estimated pen trajectory (left) compared to the actual drawing (right).

ment lengths being based on anthropometric tables.

4.2 Full arm

The second setup is based on a more complex model of the upper limb including shoulder and hand segments (cf. Figure 3 (right)). This time, the subject was asked to draw a circle.

The results, as presented in Figure 5, again clearly show similar shapes, also for this complex chain. The average distance to the plane fitted into the estimated trajectory is 0.92 cm, which is a very promising result. Also, at its main axis, the estimated trajectory has with 25.8 cm approximately the same length as the drawn circle with 27.2 cm. Nevertheless, the estimated trajectory is more ellipsoidal than the drawing. While hand and shoulder motions are here modeled and the estimated trajectory is computed including the measured pen offset, this can be attributed to remaining error sources, such as the assumed segment lengths. Also the currently unmodeled carrier angle of the lower arm can affect the result.

5. CONCLUSION AND FUTURE WORK

This paper proposes a generic approach to inertial tracking for arbitrary kinematic chains. The mathematical basis is a recursive chain formulation using DH parameters. Based on this, a state-space model compatible to any recursive filtering framework has been developed. The complete system has been implemented into a real-time tracking framework, based on which stable tracking of even complex chains has been shown through several experiments. At the same time, inaccuracies arising from uncalibrated parameters, such as segment lengths, IMU positions and carrier angles are also visible.

Consequently, future work will focus on enhancing the used calibration method to these parameters, which, however, cannot be measured from static positions. Hence, functional calibration methods, i.e. those, which include motion in the process, need to be investigated. Better modeling the anatomical properties of the human body will result in more accurate tracking of the joint angles and end effector positions. In this context, also the explicit modeling of joint limits and their handling in the estimation framework will be investigated. This requires in-depth evaluation of the tracking based on ground truth data, for which a dataset was already captured using a highly precise optical system. Finally, the scalability of the recursive solution with respect to even more complex chains will also be investigated.

6. ACKNOWLEDGMENTS

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