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# Hybrid Optical–Inertial Kalman Filter for Real–Time Human Motion Capture

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## Abstract

Human motion capture is typically performed using either optical or inertial devices. Due to their high accuracy at position level, optical marker–based systems are currently considered the gold standard [1]. However, this technology is not always the most convenient, as the setup is quite complex and costly, it is limited to a specific capture volume, and tracking and labeling of markers is often hampered by occlusions and other issues. Moreover, when the captured motion is employed as an input to inverse dynamics, velocities and accelerations must be calculated by numerical differentiation, which requires a previous filtering process whose parameters are not always easy to determine [2, 3]. Inertial systems, on the other hand, are usually more cost–effective and portable than optical ones. Besides, they are much less prone to data interruption issues, which makes them more robust. Nevertheless, they cannot estimate absolute position, only orientation, and they are sensitive to accelerations and disturbances in the magnetic field [4], which seriously impairs their accuracy in many situations.

There already exist some methods that seek to combine the positional accuracy of optical systems with the robustness and convenience of inertial ones. However, they either treat each inertial sensor as a standalone device that computes its own absolute orientation by using an onboard sensor fusion algorithm [5], which is subject to the problems mentioned above, or they use a more integrated approach that accounts for the kinematics of the whole system, but cannot operate in real time [6].

In the present work, a fully–integrated real–time motion capture system has been achieved by combining optical markers and inertial sensors within the observation function of an extended Kalman filter (EKF). The method aims to enhance the robustness of optical motion capture against marker loss, while providing a more accurate estimation of the joint torques, thanks to the incorporation of direct measurements of accelerations and angular velocities [7]. In addition, integrating inertial sensors into optical systems may also improve their portability, as it could allow drift–free full–body motion capture with a reduced set of optical markers, which would require fewer cameras.

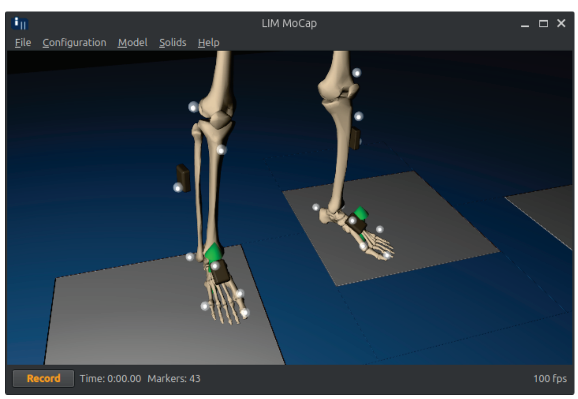


Figure 1: Lower limbs with attached markers and IMUs.

The proposed EKF is an extension to that presented in [3] and [7]. In this case, along with the optical markers, a set of inertial measurement units (IMUs) is attached to the body segments, as shown in Fig. 1. As done in [7], the state vector $\mathbf{x}$ contains the independent positions $\mathbf{z}$, velocities $\dot{\mathbf{z}}$ and accelerations $\ddot{\mathbf{z}}$ of the model. The observation function $\mathbf{h}(\mathbf{x})$, which, in the previous algorithm, provided the absolute 3D coordinates of the optical markers as a function of $\mathbf{z}$, is now augmented by adding the virtual gyroscope and accelerometer readings, $\bar{\bar{\boldsymbol{\omega}}}_s$ and $\bar{\bar{\mathbf{a}}}_s$. These magnitudes are defined in the local frame of reference of the corresponding sensor so, in order to express them as a function of the system states $\mathbf{x}$, it is necessary to determine the relative position $\bar{\mathbf{r}}_s$ and orientation $\bar{\mathbf{A}}_s$ of each IMU within the local frame of the body segment it is attached to.

The local coordinates of the IMUs are considered constant, and they can be estimated in a preliminary calibration step, by determining the positions and orientations of all the body segments and inertial sensors while the subject remains in a static pose, and then calculating the position and orientation offsets. However, obtaining the positions and orientations of the IMUs is not trivial. As mentioned before, they can estimate their own orientation by means of a sensor fusion algorithm, but they do not provide any position information. Moreover, even in the absence of accelerations, the sensor fusion algorithm may not accurately estimate the yaw angle, due to the unreliability of the magnetometers [4]. These issues can be addressed in several ways:

- Place marker clusters on the IMUs. This provides an accurate estimation of their positions and orientations, in exchange for an increase in the complexity of the optical subsystem. To alleviate this problem, the clusters can be detached from the inertial sensors once their mounting offsets have been determined.
- Place a single marker on each IMU. Then, disable the magnetometers, so the IMUs rely on gyroscope integration alone for estimating the yaw angle. Prior to attaching the IMUs to the subject, align them to the global forward axis, and reset their yaw angles to zero. Then, before the yaw estimation begins to drift, attach the sensors to the corresponding body segments, and compute their offsets $\bar{\mathbf{r}}_s$ and $\bar{\mathbf{A}}_s$, using the positions provided by the IMU markers, along with the orientations form the onboard algorithm, which should be sufficiently accurate at this point.
- Similarly, place a single marker on each IMU, but use optimization instead of sensor fusion to estimate the relative orientations $\bar{\mathbf{A}}_s$. This can be done by performing some calibration movements with all the sensors attached to the subject, then stating an optimization problem with the parameters defining the relative orientations as design variables, and the deviation between the angular velocities measured by the IMUs and those estimated from the optical system as objective function [6].

Once the positions $\bar{\mathbf{r}}_s$ and orientations $\bar{\mathbf{A}}_s$ of the IMUs within their corresponding body segments are established, the virtual sensor measurements can be properly expressed as a function $\mathbf{h}(\mathbf{x})$ of the system states. In order to achieve real–time performance, the Jacobian $\mathbf{H}(\mathbf{x})$ of the observation function is obtained analytically.

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