# Extended Kalman Filter for Real-Time, Full–Body Motion Capture and Driving Efforts Estimation

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**EXTENDED ABSTRACT**

## 1 Introduction

Real–time biofeedback has been used for years as a powerful rehabilitation tool. Many studies show that rehabilitation results can be improved with the aid of motion capture systems, force plates, electromyography probes, inertial measurement units, and other types of sensors, by allowing a patient to better adapt the movement to any kind of specified requirements through visual, auditory or haptic feedback [1].

By using complex biomechanical models, it is possible to combine the sensor measurements in order to obtain advanced biofeedback systems, even allowing to estimate muscle efforts in real time [2]. In this work, an Extended Kalman Filter (EKF) for real–time estimation of the motion and its driving forces and torques is developed. The filter is based on a previous EKF designed for real–time motion capture, using a kinematic model [3], but in this case the system dynamics are also included. Therefore, the new EKF allows to generate feedback in real time from the estimated ground reactions and joint torques, and, as an additional benefit, the motion reconstruction is improved, since the dynamics of the multibody system are now taken into account.

## 2 Multibody model

The EKF proposed in this work is based on a multibody model representing the musculoskeletal system [3], as shown in Figure 1. The model consists of 18 rigid bodies, mostly constrained by spherical joints, with a total of 52 degrees of freedom, grouped into a vector of independent coordinates $\mathbf{z}$.

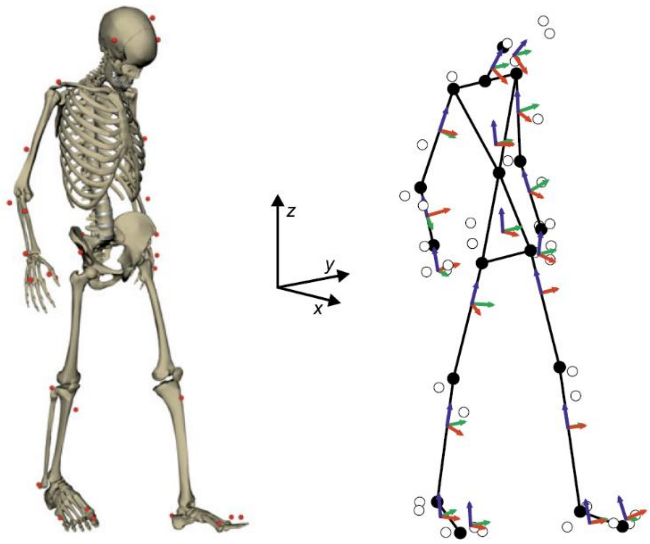


Figure 1: Multibody model

The equations of motion of the multibody system have the following form:

$$\mathbf{M}(\mathbf{z})\ddot{\mathbf{z}} = \mathbf{Q}(\mathbf{z},\dot{\mathbf{z}}) + \mathbf{B}(\mathbf{z})\mathbf{F}_e \tag{1}$$

where $\mathbf{M}$ is the mass matrix, $\mathbf{Q}$ contains the gravitational, centrifugal and Coriolis forces, $\mathbf{F}_e$ are the estimated joint torques and ground reaction forces, and $\mathbf{B}$ is a matrix that transforms the latter into generalized forces.

## 3 Extended Kalman Filter

The state vector of the Kalman filter, $\mathbf{x}$, comprises the independent coordinates of the model $\mathbf{z}$, their first time derivatives $\dot{\mathbf{z}}$, and the estimated applied forces $\mathbf{F}_e$. In order to express the state propagation model in a linear state–space form, the first step is to solve the ODE system (1) for the accelerations [4]:

$$\ddot{\mathbf{z}} = \mathbf{M}^{-1}\left(\mathbf{Q} + \mathbf{B}\mathbf{F}_e\right) \tag{2}$$

Then, the resulting equations can be linearized about a reference state, and written in linear state–space form:

$$\begin{bmatrix}\delta\dot{\mathbf{z}}\\ \delta\ddot{\mathbf{z}}\\ \delta\dot{\mathbf{F}}_e\end{bmatrix} = \begin{bmatrix}\mathbf{0} & \mathbf{I} & \mathbf{0}\\ \frac{\partial\ddot{\mathbf{z}}}{\partial\mathbf{z}} & \frac{\partial\ddot{\mathbf{z}}}{\partial\dot{\mathbf{z}}} & \frac{\partial\ddot{\mathbf{z}}}{\partial\mathbf{F}_e}\\ \mathbf{0} & \mathbf{0} & \mathbf{0}\end{bmatrix}\begin{bmatrix}\delta\mathbf{z}\\ \delta\dot{\mathbf{z}}\\ \delta\mathbf{F}_e\end{bmatrix} + \begin{bmatrix}\mathbf{0}\\ \mathbf{0}\\ \tilde{\mathbf{w}}\end{bmatrix} \tag{3}$$

where $\delta$ denotes the increment of the corresponding state variable. In this filter, $\delta\mathbf{F}_e$ will be considered as a Wiener process, so its derivative consists of continuous–time zero–mean white noise $\tilde{\mathbf{w}}$, which is introduced in the model as plant noise. By following the standard procedure to derive a discrete EKF from a continuous model, this ODE system can be discretized in time, thus providing the state transition and noise covariance matrices of the filter.

In this implementation, the system observation is carried out by two sets of sensors: 36 optical markers placed at anatomical landmarks, and two force plates, as shown in Figure 2. The observation function $\mathbf{h}(\mathbf{x})$, which provides the sensor values as a function of the state, is also nonlinear, so its Jacobian matrix must be computed in order to obtain the observation matrix $\mathbf{H}(\mathbf{x})$ of the filter.

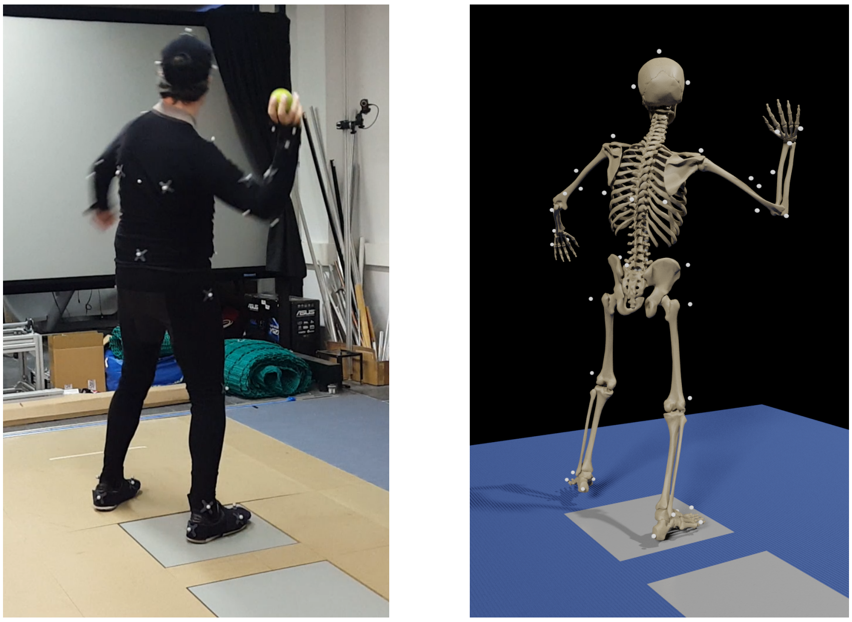

Figure 2: Motion capture using optical sensors

## 4 Conclusion

After tuning the plant and sensor noise parameters, the filter provides robust motion capture and reconstruction, while estimating joint torques and ground reactions on the fly, without the need of further post–processing. However, since the filter uses mostly position sensors, the estimation of those efforts that are not being directly measured (i.e., the joint torques) is delayed in time. The amount of delay may or may not be acceptable, depending on the biofeedback application, but it can be greatly reduced by adding gyroscopes or accelerometers to the filter, as shown in [4].

## References


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