Estimation of kinetics with unscented transformation and Kalman filters in OpenSim

Matti J. Kortelainen[1], Alexander K. Beattie[1], Paavo Vartiainen[1], and Pasi A. Karjalainen[1]
[1]HUMEA Laboratory, Department of Technical Physics, University of Eastern Finland, Kuopio, Finland
Email: matti.kortelainen@uef.fi

Summary

Conventional tools for estimation of human kinetics assume uncorrelated, zero-mean Gaussian observation noises. This limitation could be overcome by migrating the motion estimation to Bayesian framework. In this work, we perform sequential estimation of whole-body kinematics and generalized forces using unscented transformation and Kalman filters. We test this method by measuring both optical and inertial motion capture (IMU) data and ground reaction forces from test subjects performing jumping jacks. The IMU-driven solutions are compared to those obtained from optical motion capture data.

Introduction

Human motion analysis consists of multiple stages, where the outputs of previous stages are used as inputs in the next ones. Propagation of uncertainties through these stages is challenging to factor in with conventional tools based on least squares (LS) estimation, and can lead to large errors. In Bayesian framework, prior knowledge on these uncertainties can be accounted for in the estimation of posterior distributions.

Methods

We developed a Bayesian motion estimation workflow for inertial motion capture (IMU) data in OpenSim (v4.5). This workflow consists of sequential usage of unscented transformation (UT) and Kalman filters (UKF) [1, 2] to estimate whole-body kinematics and kinetics. The state estimation equations can be written as

$$\mathbf{x}_{(k)} = \mathbf{f}\left(\mathbf{x}_{(k-1)}\right) + \mathbf{w}_{(k)}, \tag{1}$$

$$\mathbf{y}_{(k)} = \mathbf{h}\left(\mathbf{x}_{(k)}\right) + \mathbf{v}_{(k)}, \tag{2}$$

$$\mathbf{z}_{(k)} = \mathbf{D}\left(\mathbf{M}\left(\mathbf{x}_{(k)}\right), \mathbf{x}_{(k)}, \mathbf{C}\left(\mathbf{x}_{(k)}\right), \mathbf{G}\left(\mathbf{x}_{(k)}\right), \mathbf{A}_{(k)}\right), \tag{3}$$

where for each time frame k, random vectors $\mathbf{x}_{(k)}$ represent kinematics of body joint angles, $\mathbf{y}_{(k)}$ IMU observations, $\mathbf{z}_k$ generalized forces, $\mathbf{w}_{(k)}$ kinematics process noise, $\mathbf{v}_{(k)}$ observation noise, $\mathbf{M}\left(\mathbf{x}_{(k)}\right)$ the system mass matrix, and $\mathbf{C}\left(\mathbf{x}_{(k)}\right)$, $\mathbf{G}\left(\mathbf{x}_{(k)}\right)$, and $\mathbf{A}_{(k)}$ the Coriolis, gravitational, and applied forces, respectively. The kinematics $\mathbf{x}_{(k)}$ are assumed to be infinitely differentiable functions which are approximated with their truncated Taylor series expansions (1) and white noise residuals [3]. Adaptive UKF produces posterior distributions for kinematics which are subsequently subjected to the computation of inverse dynamics. UT is used to estimate the distributions of $\mathbf{z}_{(k)}$ as $\mathbf{x}_{(k)}$ is input into the inverse dynamics function $\mathbf{D}(\cdot)$.

For testing, we use data measured with 12 IMUs (XSens MTw Awinda and MTW2-3A7G6; Movella Inc., USA) and Vicon motion capture system (Nexus v2.14 and Vero cameras; Vicon Motion Systems Ltd., UK) tracking full body markerset (OPT), and ground reaction force data measured with two force plates (AMTI Inc., USA). Eight test subjects perform 10 jumping jacks at the frequency of their choice while ensuring their feet land on separate force plates, starting from a standard calibration pose. The musculoskeletal (MS) model is scaled according to the anthropometry of the subject.

Using an MS model with knee adduction [4], IMU-driven kinematics are estimated using the LS solver provided by OpenSim and our UKF-based tool; in addition, OPT-driven kinematics are estimated with a corresponding OpenSim LS solver. The OPT-driven solution for the location of pelvis is used as a reference in translating the IMU-driven MS model with respect to the force plates. Generalized forces corresponding to the LS kinematics are estimated with the OpenSim inverse dynamics tool, and generalized forces corresponding to our UKF kinematics are estimated with our UT-based inverse dynamics tool. Mean absolute errors are calculated for both IMU-driven solutions for $\mathbf{z}_{(k)}$, with respect to the OPT-driven solution.

Results and Discussion

We expect the UT-based estimates for generalized forces to correspond to the gold standard OPT-driven estimates better than the IMU-driven LS estimates (measurements incomplete at the time of writing). This prospect would further warrant the usage of IMUs to carry out human motion analyses in a clinical setting. Further unrestriction of this method, i.e., to perform motion analysis outside of motion laboratories with IMUs, would require robust methods to estimate the ground reaction forces and moments from the IMU data [5].

Conclusions

Bayesian estimation of full-body kinetics is a promising development towards IMU-driven human motion analysis.

Acknowledgments

This work was supported by the Research Council of Finland under funding decision number 349469, and by the Finnish Ministry of Education and Culture's Pilot for Doctoral Programmes (Pilot project Mathematics of Sensing, Imaging and Modelling).

References

[1] Simon J. Julier. "The scaled unscented transformation". In: Proc. Am. Control Conf. Vol. 6. IEEE. 2002, 4555–4559.
[2] Eric A. Wan and Rudolph van der Merwe. "The Unscented Kalman Filter for Nonlinear Estimation". In: Proc. IEEE Adapt. Syst. Signal Process. Comm. Control. 2000, 153–158.
[3] S. Fioretti and L. Jetto (1989). *International Journal of Systems Science*, **20**: 33–53.
[4] Zachary F. Lerner et al. (2015). *Journal of Biomechanics*, **48**: 644–650.
[5] Tatsuki Koshio et al. (2024). *Sensors*, **24**: 2706.