UPPER LIMB JOINT KINEMATICS OPTIMIZATION IN REAL-TIME THROUGH A CONSTRAINED ISB-CONSISTENT MODEL

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Introduction

Real time robust upper limb joint kinematics description is a central point for several applications such as telerehabilitation and clinical evaluation. The use of wearable sensors (IMUs) together with state-of-the-art sensor fusion algorithms represents a convenient solution to unobtrusively monitor the subject performance in real-world environments. However, for long acquisitions (e.g., ~10 minutes), errors in joint angle estimates increase with time due to orientation drift thus affecting joint kinematics reliability. The aim of this work is two-fold: i) to propose a multi-segmental model of the upper limb compliant with the guidelines of the International Society of Biomechanics (ISB), ii) to propose a real-time optimization framework for the IMU-based joint kinematics estimation by setting adhoc model constraints based on both the physiological joint limits and the knowledge of the performed movement. The accuracy of the shoulder and elbow constrained kinematics was tested on one subject equipped with two IMUs during a 10-minute exercise.

Methods

A three-segment chain was designed following the Denavit-Hartenberg robotic convention to model the upper limb including the trunk, the upper arm (UA), and the forearm (FA). The shoulder and elbow joints were modeled as three $(\theta_1, \theta_2, \theta_3)$ and two $(\theta_4 \text{ and } \theta_6)$ degrees of freedom, respectively, following the ISB axis sequence. The carrying angle θ_5 was modeled as a fixed and subject specific parameter. One healthy subject was equipped with two IMUs on the UA and FA and asked to draw a continuous path with a pencil over a printed page on a horizontal surface while seated. Four reflective markers were also placed on each IMU to provide the orientation reference. IMU and marker data were recorded for ten minutes at 100 Hz. Before this, the offset of each gyroscope was subtracted from angular velocity readings. Experiments were repeated eight times with eight pairs of IMUs to test the method robustness to different IMU noise. For each time-step, the joint angles were obtained in an optimization framework by minimizing the difference between the orientation predicted using the upper limb model and the corresponding orientation computed using the sensor fusion algorithm [1] without magnetometer whose parameter was optimally tuned [2]. In addition, the optimal (θ_1 , θ_2 , θ_3 , θ_4 , and θ_6) solution had to satisfy two set of constraints. The first defined the extreme values for each θ based on the physiological joint limits. The second was determined exploiting the a priori taskspecific knowledge. In fact, during the entire recording

the elbow and wrist positions remained on a limited portion of space. Errors were computed as root mean square differences between the reference joint angles and those obtained through the optimization framework with and without applying the constraints, respectively.

Results

Average errors (deg) for θ_1 , θ_2 , θ_3 , θ_4 , and θ_6 obtained with (without) the constraints over the eight repetitions amounted to 10.9 (13.0), 6.4 (7.5), 3.9 (3.9), 14.4 (16.4), 5.4 (5.7), respectively. The average execution time to perform ~62000 iterations amounted to 9.42 ms.

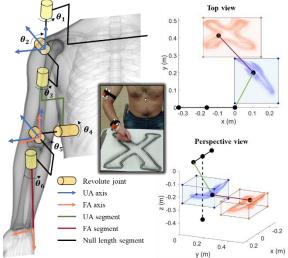


Figure 1: (left) the ISB upper limb model. (right) the boxes represent the elbow and wrist volume constraints; the point clouds represent the corresponding elbow and wrist positions estimated during the trial.

Discussion

By exploiting the knowledge of the performed movement, the constraints application allowed to reduce both shoulder and elbow angular errors by around 12% and 11%, respectively, thus limiting the impact of the IMU orientation errors on the estimated joint angles. The execution time lower than the sampling period is suitable for a real-time joint kinematics computation.

References

- 1. Madgwick et al, ICORR, 2011.
- 2. Caruso et al, Sensors, 2021.

Acknowledgements

This abstract is part of the project NODES which has received funding from the MUR – M4C2 1.5 of PNRR with grant agreement no. ECS00000036. Part of DoMoMEA project funded by Sardegna Ricerche with POR FESR 2014/2020.

