Modeling and kinematic optimization of the human upper limb for collaborative robotics

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Abstract. The emerging research field developed to optimize the collaboration of human-robot systems for Industry 4.0 gives a central role to the tracking of human motion. Inertial Measurement Units (IMUs) represent a suitable solution to unobtrusively monitor workers in the industrial environment. However, the computation of IMUs orientation usually causes drift problems and affects the kinematics estimate. Moreover, the traditional Euler angles decomposition from the mutual independent orientation of IMUs is affected by mathematical singularities and it does not include joint constraints to avoid violation of physiological motion range. To overcome these limitations, this work aimed at developing a Denavit-Hartenberg upper limb model consistent with standard biomechanical guidelines and an optimization framework for the real-time tracking of human motion. At each time step, the joint variables of the model were estimated minimizing the difference between the modeled segments orientations and those obtained with the sensor fusion. The proposed method was validated with synthetic and real robot data, verifying the influence of a considerable drift on the estimate accuracy. Finally, a comparison between the optimized joint kinematics and the one obtained with traditional methods was made.

Keywords: IMU, Industry 4.0, Human-robot Collaboration, Sensor Fusion.

1 Introduction

The fast technological development of Industry 4.0 promotes the concept of automation supporting workers with robots and realizing collaboration at different levels [1]. Accordingly, a research field focused on optimizing the performance, applicability, and effectiveness of human-robot systems has been developed [2]. To guarantee an appropriate reactive behavior by both the human and the robot, the shared workspace can be enriched with sensors for the tracking of human motion. This operation is usually performed with accurate vision devices such as stereophotogrammetric systems and RGB-D cameras [3–5]. However, problems of occlusion, encumbrance, and long set-up and calibration times make these systems inadequate for many industrial scenarios. To overcome these limitations, wearable motion capture technologies such as Magneto-

Inertial Measurement Units (MIMUs) have been introduced. Indeed, since they are portable, easy to wear, and minimally invasive, they represent a convenient solution to unobtrusively monitor subjects in their ecological environments. Consequently, MIMUs have become important tools for the real-time capturing of human motion [6–10].

Each MIMU contains a tri-axial accelerometer, a tri-axial gyroscope, and a tri-axial magnetometer on a single chip. The orientation of a MIMU with respect to a global reference frame is usually estimated through a sensor fusion process combining information of acceleration, angular velocity, and magnetic field. However, in the industrial environment, magnetometer readings can be negatively influenced by ferromagnetic disturbances. Hence, the sensor fusion process has to be performed only using IMUs signals (acceleration and angular velocity), with additional biomechanical constraints and specific calibration procedures [11, 12] to compensate for the drift on the horizontal plane. Moreover, the time integration of the angular velocity, typically corrupted by a non-stationary offset, causes drift problems in the computation of each IMU orientation [13], consequently affecting the kinematics estimate. The reduction of drift effects is usually carried out by subtracting from the angular velocity signal recorded during a dynamic acquisition the mean value registered during a static acquisition. However, this procedure is not completely effective because the offset is affected by run-to-run changes producing a residual difficult to be eliminated [13].

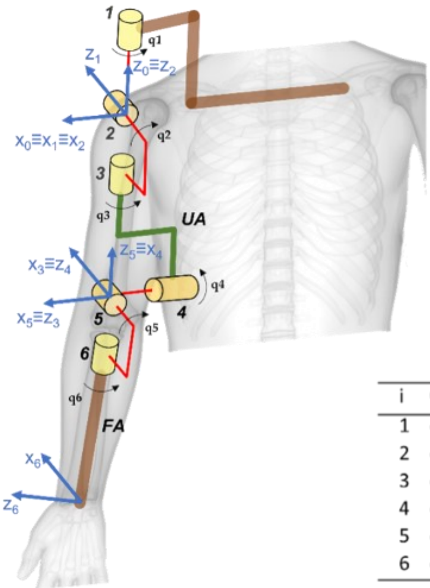
In a scenario of collaborative robotics, the accurate estimation of the human upper limb kinematics is a fundamental requirement. According to the International Society of Biomechanics (ISB), upper arm (UA) and forearm (FA) angular kinematics can be fully described with five angles and one subject-specific parameter called carrying angle [14]. This estimation is based on a previous modeling of the human upper body, identifying rigid segments connected by joints. Considering IMUs mounted on human segments, shoulder and elbow angles can be estimated by decomposing the relative orientation between consecutive IMUs into corresponding Euler angles. Even if easy and fast to apply, this technique does not consider the joints physiological range of motion nor the maximum angular change at each time step, and it is affected by mathematical singularities.

To overcome the above-mentioned limitations, the aim of this work was to propose a Denavit-Hartenberg (DH) upper limb model consistent with ISB guidelines and to develop an optimization framework enabling the real-time tracking of the human motion. This procedure allowed to set the limit for each joint and to restrict the maximum angular variation between two consecutive time steps. Values of the joints degrees of freedom (DoFs) were estimated step by step by minimizing the difference between the modeled UA and FA orientations and those assessed from IMUs with the sensor fusion algorithm. Considering the analogy between a human arm and a robotic arm [15], the proposed model was validated with synthetic and actual IMU data recorded using a robotic arm to mimic an upper limb. In both cases, the influence of a considerable drift on the estimate accuracy was verified by means of recordings of about 20 minutes. Finally, the joint kinematics obtained through the model-optimization framework and the one estimated with the traditional Euler decomposition of the relative orientation were compared.

2 Materials and methods

2.1 DH model of the human upper limb

The standard DH convention was adopted to model the human upper limb in agreement with the guidelines of ISB. A chain of two rigid links (UA and FA) was identified. A 6-DoFs model with revolute joints was defined. In detail, the shoulder was considered a spherical joint with 3 DoFs: the elevation plane angle (*q1*), the elevation (*q2*), and the intra-extra rotation (*q3*). The elbow was considered a universal joint with 2 DoFs: the flexion-extension (*q4*) and the pronation-supination (*q6*). Moreover, a fixed subject-specific carrying angle (*q5*) was introduced to model the physiological abduction of FA with respect to UA. The DH model and parameters are reported in Fig. 1.



i	θ_i	d_i	a_i	α_i
1	q1	0	0	$\pi/2$
2	q2	0	0	$-\pi/2$
3	$q3-\pi/2$	$-l_{UA}$	0	$-\pi/2$
4	$q4-\pi/2$	0	0	$-\pi/2$
5	$q5-\pi/2$	0	0	$-\pi/2$
6	$q6-\pi/2$	$-l_{FA}$	0	$-\pi/2$

Fig. 1. DH model of the human upper limb in agreement with ISB guidelines

2.2 Optimization framework

The proposed optimization framework is schematized in Fig. 2. At each time step, the process minimizes the difference between the orientation computed from IMUs through the sensor fusion algorithm ($\hat{R}_{UA}$ and $\hat{R}_{FA}$) and the orientation estimated using the DH model (R_{UA} and R_{FA}) with guess values $\boldsymbol{q}_{guess}$ of joints DoFs, for both UA and FA. The orientation residuals R_Δ for both links are represented in terms of sets of angular coordinates α, β, γ. Then, the six angular coordinates obtained for UA and FA are combined in a 3x2 matrix consisting in the objective function $f_R(\boldsymbol{q})$. A minimization process is applied to $f_R(\boldsymbol{q})$ to make the error of the estimation of $\boldsymbol{q}$ converging to zero. The output of this process is the vector of optimal values $\boldsymbol{q}_{opt}$ at each time step.

Considering the physiological range of motion of joints and, if known *a-priori*, the range of analyzed movements, limits can be identified to bound the optimal solution. Moreover, the maximum angular rate of each DoF can be constrained between two consecutive time steps. The solution convergence at each time step is promoted setting the initial guess equal to the $\boldsymbol{q}_{opt}$ values obtained at the previous time step. The minimization was implemented in MATLAB with a non-linear least squares solver.

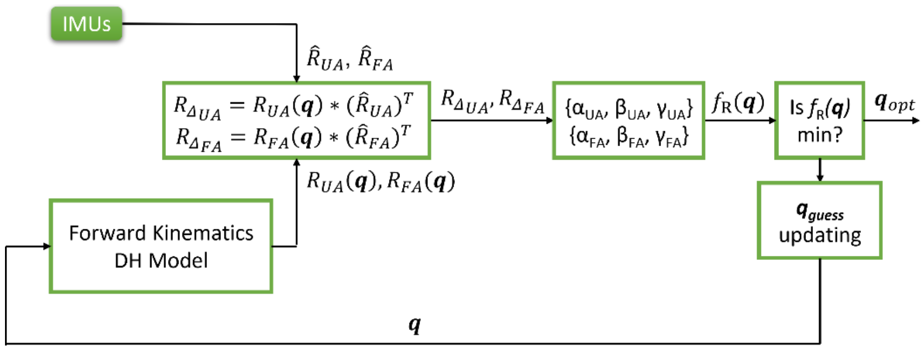


Fig. 2. Orientation-based optimization process

2.3 Data acquisition

The proposed optimization method was validated using both synthetic and robot-IMU data related to many different movements. In detail, the motion analyzed for this work involved a time variation in two DoFs, mimicking a shoulder flexion-extension and an elbow flexion-extension, simultaneously.

Synthetic data. Realistic IMU data were generated assuming the origins of both IMUs reference frames coincident with the elbow and wrist centers, and their axes aligned with (x_3, y_3, z_3) and (x_6, y_6, z_6), respectively. To simulate the desired motion, a 5th order polynomial point to point trajectory was planned varying both q_2 and q_4 from 0 to 170 deg and back in 3 s [16]. In addition, q_1, q_3, and q_6 were set to the fixed values of 90, -90, and 0 deg, respectively. The trajectory was repeated for 400 cycles (~20 minutes, sampling frequency = 100 Hz) to obtain the reference $\boldsymbol{q}_{ref}$. A recursive process linking accelerations and angular velocities to DoFs was applied to generate the corresponding ideal IMU signals. In addition, the gravity vector projected on the IMU local reference frame was subtracted from the calculated acceleration. Then, IMUs signals were corrupted with additive noise, whose characteristics (Table 1) were derived from those computed in static for 18 IMUs (Xsens MTw, The Netherlands) with the Allan Variance [17]. The static noise was generated using the IMU simulation model *Sensor Fusion and Tracking Toolbox* in MATLAB. Starting from the same seed, two static recordings were produced to simulate the gyroscope bias residual. Then, the mean value of gyroscope data estimated for the first recording was subtracted from the correspondent one of the second recording. The residuals amounted to [0.0233, 0.0270, 0.0184] and [-0.0215 -0.0076 -0.0119] dps for UA and FA gyroscope data, respectively.

Table 1. Noise characteristics for accelerometer and gyroscope.

Xsens – MTw (18 IMUs)	Accelerometer (mean + 3 STD)		Gyroscope (mean + 3 STD)	
Noise density	0.0012	$(m/s^2)/\sqrt{Hz}$	0.0079	$dps/\sqrt{Hz}$
Bias instability	0.0013	m/s^2	0.0054	dps
Random walk	6.9181×10^{-5}	$(m/s^2)/\sqrt{Hz}$	0.0004	$dps/\sqrt{Hz}$

Robot generated data. The robot arm Kinova Jaco2 was used for the framework validation with real data. The most relevant robot technical specifications are: reach = 985 mm; maximum command/s = 36 dps and 48 dps for shoulder/elbow and wrist actuators, respectively. Acquisitions were made through the software MATLAB at 100 Hz via Ethernet line. The robot has 7 joints, but its motion has been planned to generate trajectories involving only the first six DoFs, consistently to the scheme of Fig 1.

The inertial sensor system was composed of two wireless IMUs (Xsens MTw, The Netherlands), both containing a tri-axial accelerometer (range ± 160 m/s^2) and a tri-axial gyroscope (range ± 2000 dps). Once the influence of the temperature on gyroscope readings was limited through a warm-up period of 10 minutes, a static acquisition was performed to compute the gyroscope biases. Then, the two IMUs were positioned on robot UA and FA (symmetrically at 0.21 m from the elbow center). Each unit was fixed manually aligning its y-axis with the longitudinal axis of the correspondent robot link. Data were acquired through the Xsens software MT Manager (v. 4.6) at a sampling frequency of 100 Hz. Considering the previously defined DH model, the robot was programmed to move at its maximum speed from the configuration $\boldsymbol{q}_{start}$ = [90 50 -90 0 0 0] to $\boldsymbol{q}_{end}$ = [90 120 -90 150 0 0], back and forth. The robot executed the movement for 20 consecutive minutes (~ 150 cycles) actuating each joint individually.

2.4 Signal pre-processing, kinematics estimation and error evaluation

Synthetic data. The orientation of both IMUs was obtained through the sensor fusion algorithm in [18]. For each IMU, the parameter value was optimally selected by minimizing the difference between the reference and the sensor fusion orientation [19, 20].

Robot generated data. The reference joints coordinates ($\boldsymbol{q}_{ref}$) were obtained resampling robot data at a constant frequency of 100 Hz. Moreover, they were synchronized to IMU signals with the cross-correlation technique [19]. The high-frequency oscillation caused by the robot was eliminated from IMU signals through a low-pass filter (8^{th} order Butterworth, cut-off frequency equal to 4 Hz). Then, the bias computed in static was removed from gyroscope readings. Exploiting the gravity vector, IMUs were mathematically aligned to the robot surface parallel to the corresponding axes. As well as for synthetic data, IMUs orientations were obtained with a sensor fusion process using optimal parameter values and then converted into rotation matrices [18].

Both for synthetic and robot data, the $\boldsymbol{q}_{opt}$ vector was obtained by feeding the optimization framework with both model and sensor fusion-based orientation matrices. Since the motion was planar, q_1 and q_3 were bounded in the range 90 ± 1 deg, while the others were allowed to span between –5 and 160 deg. Moreover, the maximum angular change between two consecutive time steps was limited to 2 deg for q_2, q_4, and q_6, while it was forced to be null for q_5. Finally, Euler angles $\boldsymbol{q}_{Eul}$ were computed from the same orientation matrices to compare the proposed optimization and the traditional methods for the estimation of angular kinematics. The estimate accuracy was evaluated in both cases computing the following quantities: $\boldsymbol{e}_{opt}$ = rms($\boldsymbol{q}_{opt} - \boldsymbol{q}_{ref}$) and $\boldsymbol{e}_{Eul}$ = rms($\boldsymbol{q}_{Eul} - \boldsymbol{q}_{ref}$).

3 Results

The computation time (mean ± standard deviation) of the optimization process amounted to 24.4 ms ± 4.8 ms (mean frequency around 40 Hz). Table 2 contains errors for both synthetic and robot data. Fig. 3 shows the trend of q_2 and q_4, comparing the real robot kinematics to the model-driven one.

Table 2. Joint angle errors (deg).

		q_1	q_2	q_3	q_4	q_5	q_6	Mean
Synthetic	$\boldsymbol{e}_{opt}$	1.0	5.6	0.9	5.5	0	1.9	2.5
	$\boldsymbol{e}_{Eul}$	9.0	4.9	0	4.9	6.1	7.7	5.4
Robot	$\boldsymbol{e}_{opt}$	1.0	0.3	0.7	2.9	0	1.3	1.0
	$\boldsymbol{e}_{Eul}$	5.8	1.2	1.3	3.0	5.3	3.6	3.4

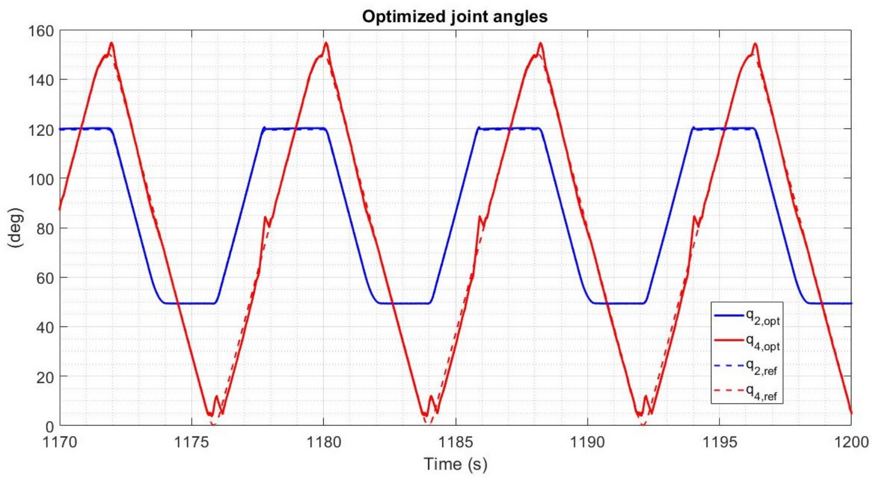


Fig. 3. Real robot kinematics vs optimized kinematics for q_2 and q_4.

4 Discussions and conclusions

In this work, an upper limb model and an optimization framework for the real-time tracking of human motion were proposed for scenarios of collaborative robotics.

Although IMUs represent a suitable solution for the joint kinematics estimate, one of their main limitations over long periods consists in the angular drift due to the integration of the gyroscope bias residuals. As highlighted in Table 2, the integration over 20 minutes can lead to a huge drift, even if residuals are low and the sensor fusion filter is driven with optimal parameter values thus reflecting the best achievable performance. Moreover, in line with [19, 20], it is interesting to observe that different scenarios (UA or FA and synthetic or robot data) require to set different optimal parameter values. Errors obtained for joint angles computed with the traditional Euler inversion (e_{Eul}) are high, especially for the DoFs estimated when IMU axes were aligned with the vertical direction during the motion. In these cases, the exploitation of the gravity direction is not sufficient to compensate for the drift. Considering the optimization framework, errors are lower (on average 2.5 vs 5.4 deg for synthetic data, 1.0 vs 3.4 deg for robot data) since motion speeds and ranges were known a-priori. In addition, errors related to robot data were in general lower when compared to synthetic ones, because the simulation was thought to be more challenging in terms of speed and intensity than the test with the robot. Finally, the proposed optimization framework could not be completely effective in reducing the drift for q_2 and q_4 as they spanned a large range of motion. However, contrary to the traditional Euler decomposition, the proposed method offers the possibility to limit variations between two consecutive time steps within reasonable values, thus mitigating the sensor fusion errors (Fig. 3). Overall, results of this study demonstrated the effectiveness of the optimization framework proposed for the real-time tracking of human motion in collaborative robotics. Current efforts are devoted to exploit the complementary information offered by linear accelerations and angular velocities. Indeed, the minimization of multiple objective functions derived from measurements with different sources of errors may improve the drift compensation [13].

References

1. Bauer, W., Bender, M., Braun, M., Rally, P., Scholtz, O.: Lightweight robots in manual assembly–best to start simply. In: Frauenhofer-Institut für Arbeitswirtschaft und Organisation IAO, Stuttgart (2016)
2. Losey, D.P., McDonald, C.G., Battaglia, E., O'Malley, M.K.: A review of intent detection, arbitration, and communication aspects of shared control for physical human–robot interaction. Appl. Mech. Rev. 70, 1–19 (2018)
3. Mainprice, J., Berenson, D.: Human-robot collaborative manipulation planning using early prediction of human motion. In: IEEE International Conference on Intelligent Robots and Systems. pp. 299–306. IEEE (2013)
4. Melchiorre, M., Scimmi, L.S., Mauro, S., Pastorelli, S.P.: Vision-based control architecture for human–robot hand-over applications. Asian J. Control. 23, 105–117 (2020)
5. Weitschat, R., Ehrensperger, J., Maier, M., Aschemann, H.: Safe and efficient human-robot collaboration part I: Estimation of human arm motions. In: Proceedings - IEEE International Conference on Robotics and Automation. pp. 1993–1999. IEEE (2018)
6. Goodvin, C., Park, E.J., Huang, K., Sakaki, K.: Development of a real-time three-

dimensional spinal motion measurement system for clinical practice. Med. Biol. Eng. Comput. 44, 1061–1075 (2006)

7. Safeea, M., Neto, P.: Minimum distance calculation using laser scanner and IMUs for safe human-robot interaction. Robot. Comput. Integr. Manuf. 58, 33–42 (2019)
8. Cereatti, A., Trojaniello, D., Croce, U. Della: Accurately measuring human movement using magneto-inertial sensors: techniques and challenges; Accurately measuring human movement using magneto-inertial sensors: techniques and challenges. (2015)
9. Digo, E., Pierro, G., Pastorelli, S., Gastaldi, L.: Evaluation of spinal posture during gait with inertial measurement units. Proc. Inst. Mech. Eng. Part H J. Eng. Med. 234, 1094–1105 (2020)
10. Digo, E., Antonelli, M., Cornagliotto, V., Pastorelli, S., Gastaldi, L.: Collection and Analysis of Human Upper Limbs Motion Features for Collaborative Robotic Applications. Robotics. 9, 33 (2020)
11. Digo, E., Gastaldi, L., Antonelli, M., Pastorelli, S.P., Cereatti, A., Caruso, M.: Real-time estimation of upper limbs kinematics with IMUs during typical industrial gestures. In: International Conference on Industry 4.0 and Smart Manufacturing (2021)
12. Škulj, G., Vrabič, R., Podržaj, P.: A wearable imu system for flexible teleoperation of a collaborative industrial robot. Sensors. 21, (2021)
13. Caruso, M., Sabatini, A.M., Knaflitz, M., Gazzoni, M., Croce, U. Della, Cereatti, A.: Orientation Estimation through Magneto-Inertial Sensor Fusion: A Heuristic Approach for Suboptimal Parameters Tuning. IEEE Sens. J. 21, 3408–3419 (2021)
14. Wu, G., Van Der Helm, F.C.T., Veeger, H.E.J., Makhsous, M., Van Roy, P., Anglin, C., Nagels, J., Karduna, A.R., McQuade, K., Wang, X., Werner, F.W., Buchholz, B.: ISB recommendation on definitions of joint coordinate systems of various joints for the reporting of human joint motion - Part II: Shoulder, elbow, wrist and hand. J. Biomech. 38, 981–992 (2005)
15. Cornagliotto, V., Digo, E., Pastorelli, S.: Using a Robot Calibration Approach Toward Fitting a Human Arm Model. Mech. Mach. Sci. 102, 199–207 (2021)
16. Siciliano, B., Sciavicco, L., Villani, L., Oriolo, G.: Robotics: Modelling, Planning and Control. Springer Verlag, London (2010)
17. El-Sheimy, N., Hou, H., Niu, X.: Analysis and modeling of inertial sensors using allan variance. IEEE Trans. Instrum. Meas. 57, 140–149 (2008)
18. Madgwick, S.O.H., Harrison, A.J.L., Vaidyanathan, R.: Estimation of IMU and MARG orientation using a gradient descent algorithm. IEEE Int. Conf. Rehabil. Robot. (2011)
19. Caruso, M., Sabatini, A.M., Laidig, D., Seel, T., Knaflitz, M., Croce, U. Della, Cereatti, A.: Analysis of the Accuracy of Ten Algorithms for Orientation Estimation Using Inertial and Magnetic Sensing under Optimal Conditions: One Size Does Not Fit All. Sensors 2021, Vol. 21, Page 2543. 21, 2543 (2021)
20. Caruso, M., Sabatini, A.M., Knaflitz, M., Croce, U. Della, Cereatti, A.: Extension of the Rigid-Constraint Method for the Heuristic Suboptimal Parameter Tuning to Ten Sensor Fusion Algorithms Using Inertial and Magnetic Sensing. Sensors 2021, Vol. 21, Page 6307. 21, 6307 (2021)