Real-time Estimate of Body Kinematics During a Planar Squat Task Using a Single Inertial Measurement Unit

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***Abstract*—This study aimed at the real-time estimation of the lower-limb joint and torso kinematics during a squat exercise, performed in the sagittal plane, using a single inertial measurement unit placed on the lower back. The human body was modeled with a 3-DOF planar chain. The planar IMU orientation and vertical displacement were estimated using one angular velocity and two acceleration components and a weighted Fourier linear combiner. The ankle, knee, and hip joint angles were thereafter obtained through a novel inverse kinematic module based on the use of a Jacobian pseudoinverse matrix and null-space decoupling. The aforementioned algorithms were validated on a humanoid robot for which the mechanical model used and the measured joint angles virtually exhibited no inaccuracies. Joint angles were estimated with a maximal error of 1.5°. The performance of the proposed analytical and experimental methodology was also assessed by conducting an experiment on human volunteers and by comparing the relevant results with those obtained through the more conventional photogrammetric approach. The joint angles provided by the two methods displayed differences equal to $3 \pm 1°$. These results, associated with the real-time capability of the method, open the door to future field applications in both rehabilitation and sport.**

***Index Terms*—Inertial measurement unit, inverse kinematics, movement analysis, squat exercise, weighted Fourier linear combiner.**

I. Introduction

THIS challenge of devising minimally invasive instrumented clinical and sport protocols for the accurate assessment of an individual's motor capacity and performance is receiving growing attention. In this context, in the last two decades, the tendency to maximize the functional information extracted from low cost and easy-to-use instruments and simplified experimental protocols has grown in the biomechanics community. For example, Cappozzo [1] defined the *minimum measured input model* framework, exemplified by the estimate of lower-limb joint mechanics during a squat exercise exploiting data provided by a single force-plate [2] or by a single inertial measurement unit (IMU) [3].

The squat exercise paradigm is considered as a very effective exercise for assessing and improving lower-limb muscle function [4]. For this reason, it has been extensively used in rehabilitation and sport training protocols. Squatting biomechanics has been investigated using kinematic and kinetic quantities in the sagittal plane. These quantities are normally estimated using data provided by a stereophotogrammetric system and force plates. However, these equipments require a considerable financial investment and implies a complex experimental setup that exclude *de-facto* its use outside the laboratory. Lately, the use of portable IMUs has allowed straightforward investigations outside the laboratory, thus allowing the enhancement of frequency and duration of the monitored exercise [5] and of its ecological traits. In addition, this technology, accompanied by adequately fast-signal processing procedures and efficient coding, may provide real-time information as required, for instance, in biofeedback applications.

If an IMU embeds a three-axis accelerometer and a three-axis gyroscope, it is in principle possible to determine its 3-D pose. However, inaccuracies in the integration of the IMU signals is unavoidable due to the presence of a time dependent drift in the signals [6]. Kalman filters have been successfully proposed in human movement analysis and reliable estimates of the 2-D IMU orientation [7] were accomplished, while the estimate of the third orientation angle and of the unit position remains problematic. Recently, an approach based on a weighted Fourier linear combiner (WFLC) has been used, while analysing quasi-periodic movements, to estimate an IMU 3-D orientation [8] and linear displacement [6], [9]. However, the assessment of the ability of this algorithm in integrating the IMU data measured during an intrinsically aperiodic movement, such us the squatting task, has not been previously performed.

IMU-based movement analysis protocols typically require the use of at least one unit per segment of interest to provide estimate of joint kinematics [5], [10]. In routine applications, however, it is desirable to reduce the number of IMUs, not only to minimize the discomfort for the user or for economic reasons, but also to avoid cumbersome calibration procedures and synchronization issues [5]. More recently, a number of studies have explored the use of single body-fixed sensors for the evaluation of spatio-temporal parameters [11] or squat task mechanics [3]. However, to the authors' knowledge, the real-time estimate of joint

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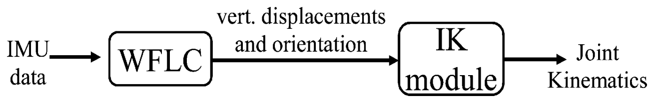

Fig. 1. General block diagram of the proposed method, using WFLC for estimating the orientation and displacement of the IMU and IK module for estimating joint kinematics.

kinematics during the execution of a task involving multiple joints, has been achieved only using multiple IMUs [5]. This is due to the difficulties of dealing with the redundancy problems related to the discrepancy between the number of kinematic quantities measured by a single IMU and the number of degrees of freedom of a multisegment mechanical model of the human locomotor system.

The robotics literature provides a number of solutions for the inverse kinematic (IK) problem in the presence of redundancies [12]–[14]. One of the most popular solutions is the so-called gradient projection method (GPM) [14]. This method allows using a suitable scalar objective function to reduce the number of possible kinematic solutions while reliable Cartesian quantities are tracked. In order to pursue the objective of the present study, a pseudoinverse matrix can be used to solve the IK problem in real time [13]. To the best of the authors' knowledge this kind of approach, able to manage redundancy problems and thus reducing the number of measured kinematic quantities, has never been used in the field of human motion analysis.

The present study shows the feasibility of a real-time estimate of lower limb and torso kinematics in the sagittal plane during a squat exercise using data collected by a single IMU. These data are then processed using the WFLC to perform a drift-free estimate of the planar sensor orientation and vertical displacement and using an IK module based on the GPM and able to manage the kinematic redundancies. The accuracy of the proposed method and its performance was assessed through *ad hoc* experiments involving both a humanoid robot and human subjects and alternative analytical and measurement methods.

II. Methods

The general method proposed for the joint kinematics estimate is illustrated in Fig. 1. Orientation and vertical displacement of the sensor, as expressed in a Cartesian space, are obtained from the data recorded with a single IMU located at the lower back using a WFLC adaptive filter. These Cartesian quantities are then provided as input to an IK module, based on a mechanical model of the portion of the locomotor system of interest, allowing the determination of the joint angles at each time sample.

The WFLC and the IK module have been designed for real-time applications and the former used for tremor cancellation [15] and the latter for the control of robotic systems [12], [13].

A. Biomechanical Model of the Human Body

The biomechanical model of the human body used in this study is shown in Fig. 2. This model was used to analyze an unconstrained body weight squat exercise in which a subject starts from an upright position, reaches a lower crouch position, and returns to the initial upright posture (see Fig. 2).

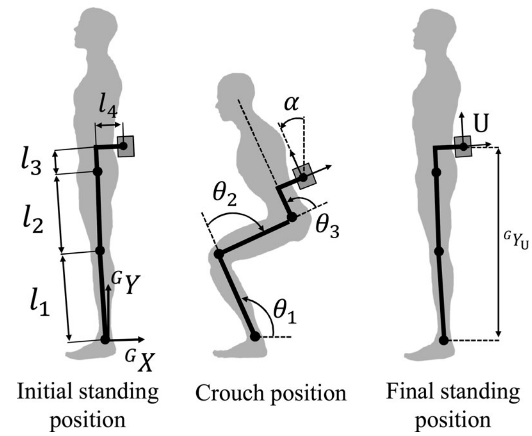

Fig. 2. 3-DOF biomechanical model of the human body. The point U represents the location of the IMU. The global frame ${}^G\mathrm{X}{}^G Y$ has its origin coinciding with the ankle joint centre and it is supposed to be stationary over the time.

The position of the IMU relatively to the ankle joint was described through a kinematic chain composed of three rigid segments (shanks (l_1), thighs (l_2), and the combined orthogonal links l_3 and l_4, with l_3 oriented as the longitudinal axis of the torso) connected by cylindrical hinges (see Fig. 2). This model implies a perfect sagittal symmetry of the exercise and rigidity of the torso-upper limbs system.

The position and orientation of the IMU, can be calculated in the global reference frame using the forward kinematic model (FKM)

$$\begin{aligned} {}^G Y_{\mathrm{U}} &= l_1 \sin(\theta_1) + l_2 \sin(\theta_1 + \theta_2) + l_3 \sin(\alpha) + l_4 \cos(\alpha) \\ {}^G X_{\mathrm{U}} &= l_1 \cos(\theta_1) + l_2 \cos(\theta_1 + \theta_2) + l_3 \cos(\alpha) + l_4 \sin(\alpha) \\ \alpha &= \theta_1 + \theta_2 + \theta_3 \end{aligned} \tag{1}$$

where θ_1, θ_2, and θ_3 are the ankle, knee and, hip joint angles, respectively, ${}^G X_{\mathrm{U}}, {}^G Y_{\mathrm{U}}$, and α describe the horizontal and vertical position, and the orientation of the IMU relatively to the global reference frame, respectively.

B. Estimate of the IMU Position and Orientation

In order to estimate the IMU position and orientation, its data need to be integrated. As previously mentioned, drift issues arise when dealing with this computation. These issues can be overcome when dealing with quasi-periodic signals using model-based adaptive filters, such as the Fourier linear combiner (FLC) filters [16], which can provide reliable estimates of an IMU 3-D orientation [10] and displacement [6], [9]. In the presence of a slightly time-varying period, as it often happens in human locomotor tasks, the WFLC filter [15] can be used to determine the time-varying amplitude $\mathbf{w}_k$ and frequency w_{0_k} weights used in the Fourier series that is used to represent the IMU signals [8].

The state vector implemented in the WFLC, $\mathbf{x}_k = [x_{1_k} \ldots x_{2M_k}]^T$, is composed of sine and cosine functions [16]

$$x_{r_k} = \begin{cases} \sin\left(r \sum_{t=0}^{k} w_{0_t}\right), & 1 \le r \le M \\ \cos\left((r-M)\sum_{t=0}^{k} w_{0_t}\right), & M+1 \le r \le 2M \end{cases} \tag{2a}$$

where M is the order of the Fourier series.

Depending on the instantaneous error ε_k between the measured signal s_k and its estimate $\hat{s}_k$, the WFLC computes the coefficients w_{0_k} and $\mathbf{w}_\mathrm{k} = [w_{1_k} \ldots w_{2M_k}]^T$ of the Fourier series using the following equations [15]:

$$\varepsilon_k = s_k - \mathbf{w}_\mathrm{k}^\mathrm{T}\mathbf{x}_\mathrm{k} - w_{b_k} \tag{2b}$$

$$w_{0_{k+1}} = w_{0_k} + 2\mu_0\varepsilon_k \sum_{r=1}^{M} m(w_r x_{M+r} - w_{M+r}x_r) \tag{2c}$$

$$\mathbf{w}_{\mathrm{k}+1} = \mathbf{w}_\mathrm{k} + 2\mu\mathbf{x}_\mathrm{k}\varepsilon_\mathrm{k} \tag{2d}$$

where μ_0 and μ are the so-called frequency and amplitude adaptation gains, respectively. To compensate for the drift effects, w_{b_k} was added in (2b) as a bias estimator, and was computed as [17]

$$w_{b_{k+1}} = w_{b_k} + 2\mu_b\varepsilon_k \tag{2e}$$

where μ_b is the bias adaptation gain.

The WFLC is usually run twice [15]: the first time to identify the frequency weight w_{0_k} and the second time using the identified w_{0_k} and a different amplitude adaptation gain (μ_FLC) to obtain the final amplitude weight estimate. Once the Fourier series coefficients are identified, the IMU position and orientation can be computed at each sample time through analytical drift-less integration [6], [9].

The sensor orientation estimate is obtained by integrating the angular velocity [6], [9] using the following equations:

$$w_{i_{r_k}} = \begin{cases} -w_{r_k}/(rw_{0_k}f_s), & 1 \le r \le M \\ w_{r_k}/((r-M)\,w_{0_k}f_s), & M+1 \le r \le 2M \end{cases} \tag{3a}$$

$$\alpha_k = \mathbf{w}_{i_k}^\mathrm{T}\mathbf{x}_k \tag{3b}$$

where f_s is the sampling frequency.

An estimate of the sensor linear displacement $\hat{P}_k$ is obtained through the double integration of the measured acceleration components

$$w_{ii_{r_k}} = \begin{cases} -w_{r_k}/(rw_{0_k}f_s)^2, & 1 \le r \le M \\ -w_{r_k}/((r-M)\,w_{0_k}f_s)^2, & M+1 \le r \le 2M \end{cases} \tag{4a}$$

$$\hat{P}_k = \mathbf{w}_{\mathbf{ii}_k}^\mathrm{T}\mathbf{x}_k. \tag{4b}$$

Having the IMU orientation α_k and the two linear displacements along the sensor axes, a rigid transformation was used to obtain the estimate of the IMU vertical displacement ${}^GY_\mathrm{U}$ in the global reference frame. Since a reliable estimate of the horizontal displacement ${}^GX_\mathrm{U}$ is hardly obtainable during a squat exercise due to the small motions of the trunk along this axis, in the rest of this paper the vector representing the Cartesian quantities inputted to the IK module will be

$$T_U(k) = \left[\,{}^GY_{\mathrm{U}_k}\ \ \alpha_k\,\right]^T.$$

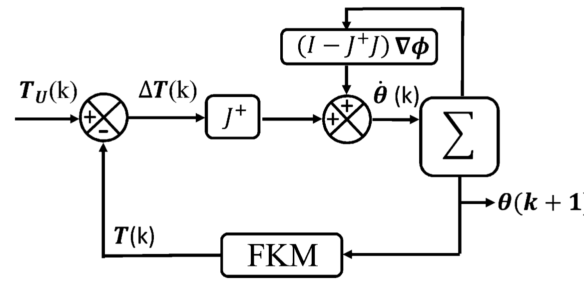

Fig. 3. Block diagram of the proposed inverse kinematic module.

C. Inverse Kinematic Module

Once the Cartesian kinematic quantities $\boldsymbol{T}_U(\mathrm{k})$ have been collected from the IMU data, the IK problem consists in finding the joint trajectories $\boldsymbol{\theta}(k)$ that make the tracking error $\Delta\boldsymbol{T}(k) = \boldsymbol{T}_U(k) - \boldsymbol{T}(k)$ (i.e., the difference between $\boldsymbol{T}_U(\mathrm{k})$and its current estimate $\boldsymbol{T}(k)$ obtained from the forward kinematic model (FKM)) equal to zero. In the case of a squat task and using the proposed biomechanical model and measuring instrument (see Fig. 2), the system is redundant, since it has 3-DOF whereas only two quantities can be reliably estimated in the Cartesian space. This problem can be solved in its close-loop form (see Fig. 3) by numerically solving a system of linear equations describing the relationship between the Cartesian velocities ($\Delta\boldsymbol{T}$) and the joint angular velocities $\dot{\boldsymbol{\theta}}$. The advantage of this approach is that it allows for handling regular, singular, and redundant cases in a unified way [12]. Among the possible implementation of the IK problem, the GPM [14] was chosen for this study, in which a local solution at velocity level is sought through the use of the pseudoinverse Jacobian matrix and the projection of the homogeneous solution onto the null space of the Jacobian matrix.

The general solution of the IK problem in the redundant case can be written as [12]–[14]

$$\dot{\boldsymbol{\theta}}(k) = \boldsymbol{J}^+\Delta\boldsymbol{T}(k) + (\boldsymbol{I} - \boldsymbol{J}^+\boldsymbol{J})\boldsymbol{\nabla\phi} \tag{5}$$

where $\boldsymbol{J}, \boldsymbol{J}^+$, and $\boldsymbol{I}$ are the Jacobian matrix, its pseudoinverse, and the identity matrix, respectively, and $\phi(\theta)$ is a scalar function that allows for selecting a joint configuration among the infinite solutions. The so-called null space vector $\boldsymbol{\nabla\phi} = \left[\frac{\partial\phi}{\partial\theta_1}\,\frac{\partial\phi}{\partial\theta_2}\,\frac{\partial\phi}{\partial\theta_3}\right]^T$ allows for minimizing $\phi(\theta)$ independently from the tracking of $\boldsymbol{T}_U$ [12].

The continuous and differentiable scalar function $\phi(\theta) = \phi_j(\theta) + \phi_U(\theta)$ used in the GPM is composed by two scalar functions $\phi_j(\theta)$ and $\phi_U(\theta)$ representing the biomechanical constraints associated to the squat task. The function $\phi_j(\theta)$ is used to generate a set of joint trajectories away from the joints upper ($\boldsymbol{\theta}_{ub}$) and lower ($\boldsymbol{\theta}_{lb}$) limits and evolving preferentially close to the mean value of the range of motion

$$\phi_j(\theta) = \beta_j\left(\frac{1}{e^{(\gamma(\boldsymbol{\theta}-\boldsymbol{\theta}_{lb}))^2}} + \frac{1}{e^{(\gamma(\boldsymbol{\theta}-\boldsymbol{\theta}_{ub}))^2}}\right) \tag{6}$$

TABLE I
JOINT LIMIT VALUES USED IN THE IK MODULE

	Upper limit ($\boldsymbol{\theta_{ub}}$) [deg]	Lower limit ($\boldsymbol{\theta_{lb}}$) [deg]
θ_1	125	85
θ_2	5	-100
θ_3	110	-15

where γ and β_j are constant parameters.

Upper and lower joint limits (see Table I) were empirically set in accordance with observed joints range of motion during the squat exercise.

The function ϕ_U is used to constrain the horizontal displacement of the IMU ${}^G X_{\mathrm{U}}$ around its initial position

$$\phi_U(\theta) = \beta_U \left({}^G X_{\mathrm{U}} - {}^G X_{\mathrm{U}_0}\right)^2 \tag{7}$$

where ${}^G X_{\mathrm{U}_0}$ is the horizontal coordinate of the IMU at the first instant of time and β_U is a constant.

At the beginning and at the end of the squat cycle, where the joints are aligned, the system is close to a singular position (see Fig. 2). The presence of unavoidable kinematic singularities and/or of unreachable Cartesian coordinates, due to modeling error and/or inaccuracies in the estimate of $\boldsymbol{T}_U$ provided by the WFLC algorithm, can lead to discontinuity of the closed-loop scheme described in Fig. 3. To overcome these issues a damped least-square inverse of the Jacobian matrix can be introduced in (5) [18]:

$$\boldsymbol{J}^+ = \boldsymbol{J}^T(\boldsymbol{J}\boldsymbol{J}^T + \lambda^2 \boldsymbol{I}) \tag{8}$$

whereλ is the damping coefficient, computed using the minimum singular value of the Jacobian matrix [19], $\sigma_{\min}$ which represents the exact measure of the proximity with a singularity [13]

$$\begin{cases} \lambda = \varepsilon^2 - \sigma_{\min}^2 & \text{if } \sigma_{\min} \le \varepsilon \\ \lambda = 0 & \text{if } \sigma_{\min} > \varepsilon \end{cases} \tag{9}$$

where ε is a positive constant threshold value.

Once (5) is solved, the joint angles can be finally computed integrating the instantaneous joint velocities

$$\boldsymbol{\theta}(k+1) = \boldsymbol{\theta}(k) + \dot{\theta}(k)/f_s. \tag{10}$$

D. Optimal Parameters Identification

1) WFLC Algorithm: Data recorded from two randomly selected subjects according to the squat protocol described in the following section, were used to determine the optimal combination of M values and of the WFLC gains μ, $\mu_F LC, \mu_0$, and μ_b providing the best estimate of $\boldsymbol{T}_U$.

For each value of M ranging from 1 to 15, two different identification processes were run. The first one aimed at determining the parameters that ensure an accurate estimate of the sensor orientation α and minimize an objective function J_α based on the least square difference between the measured sensor orientation α_m and its estimate over 20 squat cycles

$$J_\alpha = \frac{1}{20} \sum_{\mathrm{SC}=1}^{20} \left(\frac{1}{N} \sum_{i=1}^{N} (\alpha_m(i) - \alpha(i))^2 \right) \tag{11}$$

where N is the number of samples recorded for each squat cycle.

Similarly, a second cost function J_Y is minimized to determine the parameters for the optimal estimate of the sensor vertical displacement:

$$J_Y = \frac{1}{20} \sum_{\mathrm{SC}=1}^{20} \left(\frac{1}{N} \sum_{i=1}^{N} \left({}^G Y_{\mathrm{U}_{km}}(i) - {}^G Y_{\mathrm{U}_k}(i)\right)^2 \right) \tag{12}$$

where ${}^G Y_{\mathrm{U}_{km}}$ is the vertical displacement of the sensor measured by the stereophotogrammetric system.

A Levenberg–Marquardt algorithm [20] was used to solve these identification processes with the same initial conditions for all trials, where the gains were set to zero. Considering that the average task duration was $T = 2$ s, w_{0_1} was set as $w_{0_1} = 2\pi/T = \pi$ rad.s^{-1}.

2) Tuning of the IK Module: Data recorded from the same two previously selected subjects were used to determine the optimal value of parameters, γ, β_j, and β_U used for solving the IK problem. To this purpose, the following cost function was minimized

$$J_\theta = \frac{1}{20} \sum_{SC=1}^{20} \left(\frac{1}{N} \sum_{i=1}^{N} (\theta_{m_{1,2,3}}(i) - \theta_{1,2,3}(i))^2 \right) \tag{13}$$

where $\theta_{m_{1,2,3}}$ refers to the measure of the three investigated joint angles and $\theta_{1,2,3}$ to their estimate by the proposed method.

The threshold coefficient ε used in the calculation of the damping factor was set to $\varepsilon = 0.05$. This value was determined by calculating $\sigma_{\min}$ using all the measured joint angles while the subjects were close to upright posture, i.e., close to the kinematic singularities.

E. Robot Experiment

A HOAP-3 humanoid robot (*Fujitsu*) was used to assess the accuracy of the proposed methodology under a virtually perfect consistency between reality and the biomechanical model depicted in Fig. 2. Six joints of the lower limb of this 21-DOF humanoid robot (height: 0.6 m, mass: 8.8 kg) were controlled to generate a squat motion in the sagittal plane. The robot motion was played in open-loop using a pure sinusoidal trajectory (main frequency 0.5 Hz) for each joint. The amplitudes of the sinusoidal trajectories were chosen to ensure the balance of the robot while producing a human-like squat motion (see Fig. 4). Actual joint angles were recorded (1000 samples/s) by embedded joint encoders at a resolution of 0.0048°. An IMU (*MTx, Xsens Motion Technologies*) was rigidly mounted on the back of the robot as illustrated in Fig. 4. The geometric parameters of the mechanical model associated to the HOAP-3 robot were as follows: $l_1 = l_2 = 0.105$ m, $l_3 = 0.252$ m, and $l_4 = 0.107$ m.

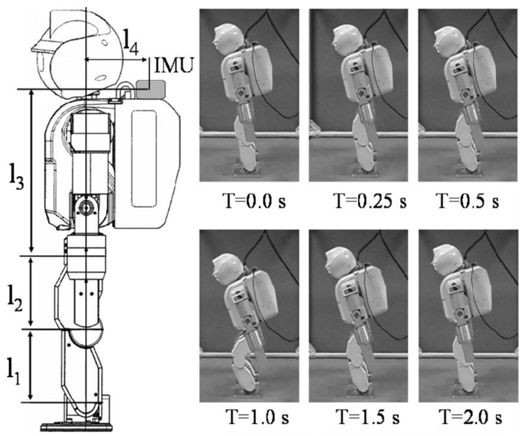

Fig. 4. Hoap-3 Humanoid robot and its squat movement.

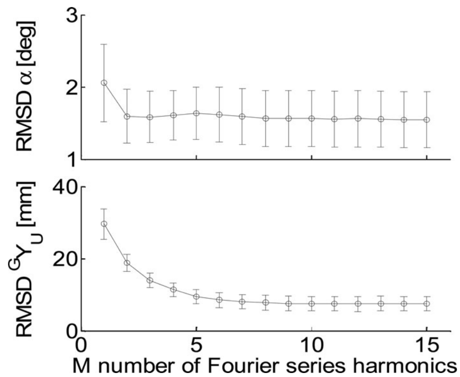

Fig. 5. Effects of the variation of the order of the Fourier series on the accuracy of the IMU orientation and vertical displacement estimates.

F. Human Subject Experiment

The proposed method was also assessed using human volunteers. In this case, the discrepancy between the results provided by the latter approach and the more cumbersome stereophotogrammetric approach was highlighted. Eight healthy volunteers (five males and three females, age $= 32.5 \pm 9.9$ years, mass $= 69.3 \pm 6.8$ kg, stature $= 1.74 \pm 0.33$ m) participated in the study after signing an informed consent form.

The same IMU used for the robot experiment was secured to the lower back of the subjects and aligned with the anatomical axes of the lower trunk. Three retro reflective markers were attached to the IMU to validate its pose estimation. Care was taken to fix the IMU to the lower trunk so as to minimize its motion relative the underlying skeleton. Residual artefact movements cannot be compensated for and contribute to the inaccuracy of the method.

As shown by an earlier study [3], the investigated squat exercise, as performed by able-bodied individuals, displays sagittal symmetry. Consequently, markers were located on the following right anatomical landmarks: lateral malleolus, lateral femoral epicondyle, and acromion. In addition, markers were placed on the anterior and posterior superior iliac spines on both sides. The latter markers allowed the determination of a pelvic anatomical frame and of the position of the hip joint centre in that frame through published regression equations [21]. The 3-D trajectories of the reflective-markers were recorded using a nine-camera stereophotogrammetric system (MX, VICON).

The joint angles and segment lengths associated with the mechanical model defined in Fig. 1 were calculated using the instantaneous positions of the above-mentioned ankle, knee and shoulder anatomical landmarks and of the estimated hip joint centre. The initial joint angles measured while the volunteers were standing in their natural posture were used to determine the initial value of α and ^GY_U. Volunteers were asked to execute an unconstrained squat exercise at self-selected speed, keeping their arms straight along their sides and their feet flat on the ground. Ten trials were performed by each volunteer, with rests between the trials.

G. Data Analysis

The Root Mean Square Difference, RMSD, and the correlation coefficient, r, between the investigated kinematic variables as obtained with reference instruments (motor encoders for the HOAP-3 robot and stereophotogrammetric system for the human data) and those obtained with the IMU data were calculated. For the experiment on human subjects the RMSD and r values were computed for the 60 squat trials that had not been used for the parameters identification.

III. Results

A. Optimal Parameters Identification

The results optimization processes concerning the choice of M and of the other WFLC parameters on the estimate of the IMU orientation and vertical displacement are illustrated in Fig. 5, which shows the corresponding RMSD.

To minimize the computational time and guarantee for the algorithm stability, M should be set to its lowest possible value. Since, as deducible from Fig. 5, values higher than $M = 2$ for the orientation and $M = 7$ for the vertical displacement did not lead to significant improvements in terms of RMSD values, this latter value was chosen for the rest of the analysis. The corresponding optimal values of the WFLC gains were $\mu = 2e^{-2}$, $\mu_{\mathrm{FLC}} = 0.12$, $\mu_0 = 3e^{-5}$, $\mu_b = 1e^{-4}$for the orientation α and $\mu = 8e^{-3}$, $\mu_{\mathrm{FLC}} = 4e^{-2}$, $\mu_0 = 1e^{-6}$, $\mu_b = 2e^{-7}$for the vertical displacement ^GY_U. The optimal combination identified for the coefficients of the IK module provided the following values: $\gamma = 1.2e^2$, $\beta_j = -1$, and $\beta_U = -2e^{-2}$.

B. Robot Experiment

As expected, since the squat task executed by the HOAP-3 robot was perfectly periodic, the estimate of orientation and vertical displacement of the IMU was highly accurate with a RMSD of α and of ^GY_U equal to 0.24° and to 0.3 mm, respectively. The estimate of the joint angles was accurate, even if a slight error is introduced by the IK module due to the unavoidable kinematic singularities, i.e. at the beginning and at the end of the squat task (see Fig. 6). The RMSD and r values

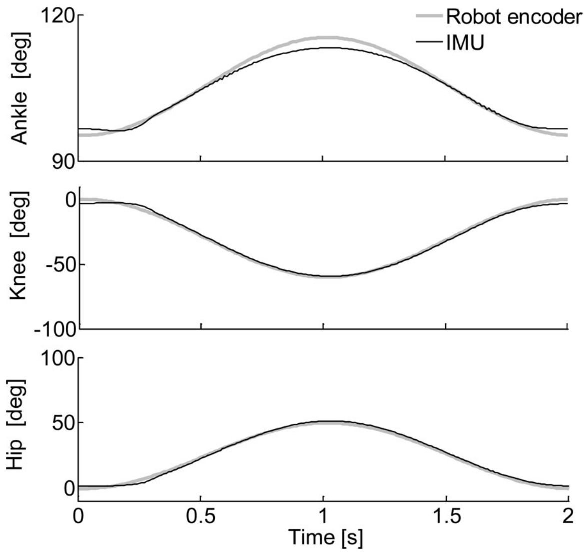

Fig. 6. Results obtained for the joint angles of interest in the squat task performed by the HOAP-3 humanoid robot.

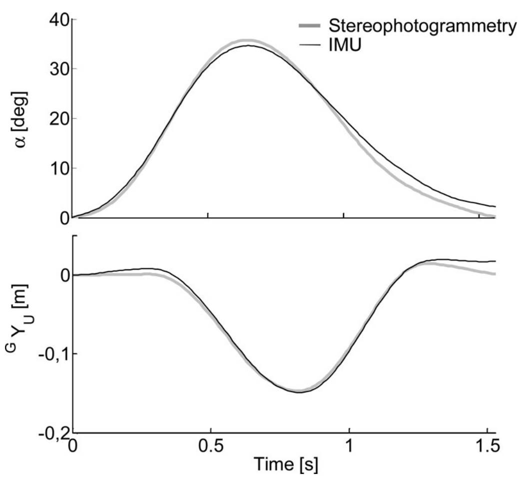

Fig. 7. Representative results showing the estimates of the IMU orientation $\alpha$and vertical displacement $^G Y_U$ obtained for one randomly chosen subject. The corresponding RMSD were $\alpha = 1.8°$, $^G Y_U = 7$ mm.

were 1.0°and 0.998 for the ankle, 1.4° and 0.998 for the knee, and 1.3° and 0.997 for the hip, respectively.

C. Human Subject Experiment

As shown in Figs. 7 and 8, for one randomly selected trial, the proposed algorithm led to estimates of the IMU orientation and vertical displacement and of the ankle, knee, and hip joint flexion and extension angles during the whole squat exercise that were very similar to those obtained with the stereophotogrammetric system.

The mean (standard deviation), RMSD and r values computed for the 60 trials that were not previously used for the identification of the optimal parameters are reported in Table II. For all the recorded squat exercises, the angles of interest were estimated with an average difference from the stereophotogrammetric data of less than 3.5° and with average correlation coefficients greater than 0.9 (with relevant p-values being all smaller

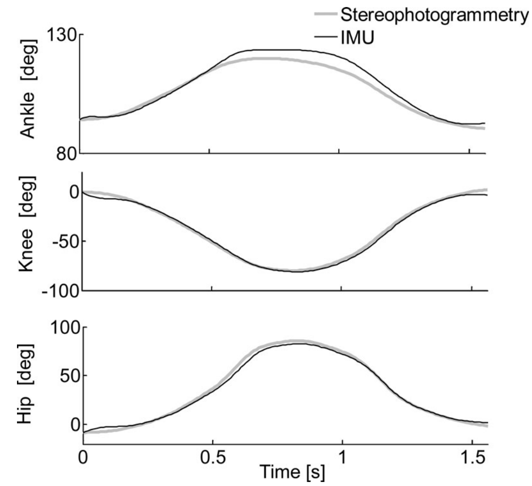

Fig. 8. Representative results showing the joint angles obtained for one randomly chosen subject. The corresponding RMSD were $\theta_1 = 2.9°$, $\theta_2 = 2.2°$, and $\theta_3 = 2.6°$.

TABLE II
HUMAN SUBJECTS EXPERIMENTS: SUMMARY OF THE RESULTS

	RMSD	*R*
α (IMU orient.)	2.0±1.5 deg	0.89±0.24
$^G Y_U$ (IMU vert. disp.)	9±5 mm	0.99±0.00
θ_1 (ankle joint)	3.2±1.0 deg	0.99±0.00
θ_2 (knee joint)	2.0±1.0 deg	0.99±0.00
θ_3 (hip joint)	3.1±0.9 deg	0.99±0.00

than 1e–7). The highest differences were observed at the ankle joint.

IV. DISCUSSION

This study proposed a method for the estimate of the lower-limb joint and trunk kinematics in the sagittal plane during a squat exercise using only one single inertial measurement unit located at the lower back. The method lends itself to the real-time applications.

The experimental validation performed with a HOAP-3 humanoid robot provided a simplified situation, with accurate knowledge of the mechanical system geometry, no experimental artifacts, and an actual periodic planar motion. The proposed method was successfully tested, as demonstrated by a RMSD lower than 1.5° for all investigated joint angles. The RMSD is mainly due to the IK module and might be explained by the fact that, this module, due to the use of the damped least-squares pseudo-inverse Jacobian matrix, smooths the joint angles when working in proximity of a singular configuration. The differences in the accuracy observed between the three joints might be due to the fact that the current implementation of the pseudo-inverse matrix gives the same importance to each of them, whereas a proper weighting might improve the results. Further studies are needed to test this hypothesis.

The use of parameters optimized for the application of the WFLC algorithm to the squat task, allowed its convergence within few samples and provided an accurate integration of the angular velocity data even if the analysed movement was described by a relatively small number of samples.

The experiments on human subjects and the comparison with the stereophotogrammetric system (see Table II) showed that orientation and vertical displacement of the IMU and ankle, knee, and hip joint kinematics can be estimated by the proposed method with relatively small differences. The RMSD of the orientation was around 2° and that of the vertical displacement around 10 mm. This was obtained thanks to the fact that the proposed WFLC implementation avoids the use of error-prone numerical integration algorithms. The range of RMSD of the estimate of the lower limb joint angles was similar to what has been obtained in other studies using one or more IMUs per body segment (0.4–4°) [5], [10]. The latter approaches provide accurate results, also for 3-D tasks, but rely on complicated experimental procedures, typically requiring the assistance of an expert operator.

The chosen biomechanical model poses theoretical limits that might have affected the quality of the results. In fact, if the squat task had been performed with large movements in the frontal and transverse planes, the planar assumption of the movement would have not been valid anymore. In principle, provided that the 3-D movements of the IMU can be estimated through the WFLC, this issue maybe overcome using a different biomechanical model together with a 3-D IK module. Future studies will focus on this approach.

In its current Matlab implementation, the computational time of the proposed method is in the order of 50 ms and can be made 20 times lower through proper programming optimization. This time delay is lower than the time lapse that would make the user feel that the system is reacting instantaneously [22] and, in any case, within the sampling interval of the normally used biofeedback tools such as video projectors. The exploitation of IMU along with real-time applications of the proposed method will be the target of future activity.

References

[1] A. Cappozzo, “Minimum measured-input models for the assessment of motor ability,” *J. Biomech.*, vol. 35, pp. 437–446, 2002.

[2] C. Mazzà and A. Cappozzo, “An optimization algorithm for human joint angle time-history generation using external force data,” *Ann. Biomed Eng.*, vol. 32, pp. 764–772, 2004.

[3] V. Bonnet, C. Mazzà, P. Fraisse, and A. Cappozzo, “A least-squares identification algorithm for estimating squat exercise mechanics using a single inertial measurement unit,” vol. 45, pp. 1472–1477, 2012.

[4] A. C. Fry, J. C. Smith, and B. K. Schilling, “Effect of knee position on hip and knee torques during the barbell squat,” *J. Strength Cond. Res.*, vol. 17, pp. 629–633, 2003.

[5] D. T. P. Fong and Y. Y. Chan, “The use of wearable inertial motion sensors in human lower limb biomechanics studies: A systematic review,” *IEEE Sensors J.*, vol. 10, pp. 1556–1565, 2010.

[6] U. X. Tan, K. C. Veluvolu, W. T. Latt, C. Y. Shee, C. N. Riviere, and W. T. Ang, “Estimating displacement of periodic motion with inertial sensors,” *IEEE Sensors J.*, vol. 8, pp. 1385–1388, 2008.

[7] C. Mazzà, M. Donati, J. McCamley, P. Picerno, and A. Cappozzo, “An optimized Kalman filter for the estimate of trunk orientation from inertial sensors data during treadmill walking,” *Gait and Posture*, vol. 35, pp. 138–142, 2011.

[8] V. Bonnet, J. McCamley, C. Mazzà, and A. Cappozzo, “Trunk orientation estimate using gyroscope sensors,” in *Proc. 4th IEEE RAS/EMBS Int. Conf. Biomed. Robot. Biomechatronics*, Roma, Italy, Jun. 2012, pp. 367–372.

[9] W. T. Latt, K. C. Veluvolu, and W. T. Ang, “Drift-free position estimation of periodic or quasi-periodic motion using inertial sensors,” *IEEE Sensors J.*, vol. 11, pp. 5931–5951, 2011.

[10] F. Bagala, V. L. Fuschillo, L. Chiari, and A. Cappello, “Calibrated 2D angular kinematics by single-axis accelerometers: From inverted pendulum to N-Link chain,” *IEEE Sensors J.*, vol. 12, pp. 479–486, 2012.

[11] J. McCamley, M. Donati, E. Grimpampi, and C. Mazzà, “An enhanced estimate of initial contact and final contact instants of time using lower trunk inertial sensor data,” *Gait and Posture*, vol. 36, pp. 316–318, 2012.

[12] B. Siciliano, “Kinematic control of redundant robot manipulators: A tutorial,” *J. Int. Robot. Syst.*, vol. 3, pp. 201–212, 1990.

[13] W. Khalil and E. Dombre, *Modeling, Identification and Control of Robots*. San Diego, CA, USA: Kogan Page Science, 2004.

[14] A. Liegeois, “Automatic supervisory control of the configuration and behavior of multibody mechanisms,” *IEEE Trans. Syst., Man, Cybern.*, vol. 7, pp. 868–871, 1977.

[15] C. N. Riviere, R. S. Rader, and N. V. Thakor, “Adaptive cancelling of physiological tremor for improved precision in microsurgery,” *IEEE Trans. Biomed. Eng.*, vol. 45, pp. 839–846, 1998.

[16] C. A. Vaz, X. Kong, and N. V. Thakor, “An adaptive estimation of periodic signals using a Fourier linear combiner,” *IEEE Trans. Signal Process.*, vol. 42, pp. 1–10, 1994.

[17] K. C. Veluvolu, W. T Latt, and W.T. Ang, “Double adaptive bandlimited multiple Fourier linear combiner for real-time estimation/filtering of physiological tremor,” *Biomed. Signal Process.*, vol. 5, pp. 37–44, 2010.

[18] Y. Nakamura and Y. Hanafusa, “Inverse kinematic solutions with singularity robustness for robot manipulator control,” *Trans. ASME, J. Dynam. Syst., Meas. Control*, vol. 108, pp. 163–171, 1986.

[19] A. A. Maciejewski and C. A. Klein, “The singular value decomposition computation and applications to robotics,” *Int. J. Robot. Res.*, vol. 8, pp. 63–79, 1989.

[20] D. Marquardt, “An algorithm for least-squares estimation of nonlinear parameters,” *SIAM J. Appl. Math.*, vol. 11, pp. 431–441, 1963.

[21] A. L. Bell, D. R. Pedersen, and R. A. Brand, “A comparison of the accuracy of several hip center location prediction methods,” *J. Biomech.*, vol. 23, pp. 617–621, 1990.

[22] R. B. Miller, “Response time in man-computer conversational transactions,” in *Proc. AFIPS Fall Joint Computer Conf.*, 1968, vol. 33, pp. 267–277.

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