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## Gait analysis using optimality criteria imputed from human data

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**Abstract:** This study proposes an efficient and automatic tool to understand and analyze the human natural and fast gait tasks. First, the gait tasks are modeled as a nonlinear optimal control problem along with a nonlinear model predictive control, usually used in the humanoid robots control. Second, under the assumption that the walking motions are the result of an optimization process, the identification of plausible optimality criteria weight values is achieved with an inverse optimal control (IOC) approach. Our IOC walking scheme is performed on ten subjects with ten trials for each gait task considered. Results show that the variability observed in the experimental data are exhibited by our proposed scheme. Finally, an easy distinguish can be made between the gait tasks only by checking out the exhibited criteria weight values.

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**Keywords:** Optimal control theory, Inverse optimal control, Modeling for control optimization, Identification and control methods, Human walking control, Trajectory and Path Planning.

### 1. INTRODUCTION

Understanding human walking arises in several areas of study in robotics such as motion generation and control of humanoid robots, human-robot interaction, design and control of exoskeletons or prostheses. One way of achieving some insights is from the experimental data of human walking by motion capture systems, measurements of external forces (force plates), EMG recordings etc. Nevertheless, there are many walking parameters which are not available, such as center of mass position, joint torques etc. In this context, accurate dynamic human models are proposed in literature such as dynamic whole-body models (Felis et al. (2015)) or models which are generally used in humanoid robots control (Aftab et al. (2012)) to capture and gain access to the walking parameters of interest.

Over the last decades, human walking motions are considered to be the result of an optimization process where one or multiple optimality criteria are minimized (Alexander (1984)). Under this hypothesis, the optimality criterion/criteria minimized by the human motor control remain(s) unknown. One way towards the identification of these assumed optimality criteria for human walking motion can be achieved by considering the inverse optimal control (IOC) problem. The latter was already used in the literature to understand human walking behaviour and one can find it solved with different approaches, such as the bi-

level approach (Clever et al. (2016)) or the approximately optimal control approach (Papadopoulos et al. (2015)). The latter studies the human body by using the dynamics of an unicycle robot type (Mombaur et al. (2010)) or by considering it a hybrid dynamic multi-body system with several degrees of freedom (Mombaur et al. (2013)).

Being interested in gaining some insights from human natural and fast walking behaviours, the goal of our study is **first**: to propose an effective simplified modeling for the tasks and **second**: to identify plausible optimality criteria in an optimal control framework.

In our study, the human body is modeled by making use of the previously employed walking patterns for the design and the control of humanoid robots. These kind of walking patterns (Carpentier et al. (2016), Naveau et al. (2016)) consist on a nonlinear optimization problem based on a model predictive control (MPC) scheme, as suggested in Herdt et al. (2010). The inconvenient in the latter studies consists in the random selection of the optimality criteria weight values. The latter motivated us to make use of the IOC problem, along with a nonlinear optimization problem for the human body modeling, and propose an efficient and automatic scheme of identifying the optimality criteria weight values.

We propose to impute such optimality criteria from human natural and fast walking motions, by using the improved version of the inverse Karush-Kuhn-Tucker (KKT) approach as proposed in Panchea (2015) or Lin et al. (2016). Then, the identified criteria weight values are used in the

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nonlinear optimization modeling scheme to predict gait parameters, such as step positions and durations along with both the kinematics and dynamics of the center of mass and of the center of pressure. Our proposed IOC walking scheme can be considered for humanoid robots control or in clinical decisions, rehabilitation, therapy sciences and all sciences with interest in predicting human behaviour, with the advantage of an automatic choice on the optimality criteria weight values. Along with this long list of potential applications and advantages we can also add the fact that these automatic criteria weight values imputed from human motions can be used to replicate, to understand and to distinguish between natural and fast human walking behaviour.

The organization of this paper is as follows. In Sect. 2, the human natural and fast walking tasks and the way we reconstruct the CoM position is described. Sect. 3, presents the human walking model, while Sect. 4 summarizes the inverse KKT approach. Experimental data results of our IOC walking scheme are given in Sect. 5 while Sect. 6 ends the study with conclusions and future work.

## 2. HUMAN WALKING TASKS DESCRIPTION

Ten healthy subjects without any known locomotion degenerative diseases agreed to reproduce the walking tasks. Subjects, barefoot and standing upright and motionless on a force plate level with the ground, were instructed to perform walking following a beep delivered by the experimenter. Two experimental walking conditions are tested: (1) the *natural gait condition* (denoted *NGC*) where subjects walked normally, and (2) the *fast gait condition* (denoted *FGC*) where subjects walked as fast as they could. Each subject performed 10 trials for each condition and only the first two steps are analyzed.

**Center of pressure (CoP).** A force platform operating at a sampling rate equal to 2000 *Hz* is used to record the first two steps exerted by the subjects during the walking task and to provide the ground reaction forces and moments with respect to the medio-lateral, antero-posterior, and vertical axes of the force plate. Such information allows the access to the center of pressure position trajectory, step lengths and CoM position, velocity and acceleration. First, the CoP position is interpolated and, second, we'll make use of the resulted interpolated and filtered CoP position to reconstruct the CoM using the dynamics of a cart on table (Kajita et al. (2003)), as reported later. We carry out B-spline interpolation techniques for the CoP position curve in order to filter and to re-sample the actual data. B-spline basis functions are defined by piecewise polynomials capable of modeling observations by providing two types of independent controls: a set of fixed control points (knots) and spline degree. The degree of the B-spline used depends on the desired order of derivative. Generally a spline of  $r^{th}$  order can be differentiated  $(r - 2)^{th}$  times. For instance, if we require a smooth jerk curve, then B-splines of degree 5 and above should be used.

In our study, the number of B-splines knots and degree are chosen empirically to be 600 and 5, respectively. The interpolated CoP position curve resulted in the  $R^2$  statistic above 96% for most of the time-series features.

**Center of mass (CoM).** A way towards rebuilding the CoM position is by making use of Kajita's walking pattern (Kajita et al. (2006)). Therefore, we reconstruct the CoM by using the cart on table dynamics as proposed in Kajita et al. (2006), where the CoP position is computed from the ground reaction force given by the force platform:

$$p = c - \frac{h}{g} \ddot{c},$$

where  $p$  is the CoP,  $c$  and  $\ddot{c}$  are the CoM position and acceleration,  $h$  is the altitude,  $g = 9.8 [m/s^2]$  is acceleration due to gravity.

**Step length.** The step positions ( $X_f = [L_1 \ L_2]$ ) were measured from the antero-posterior CoP displacement between its initial position and its position at the second foot-off time of the stance leg (determined by the sudden arrest of the anterior displacement of the CoP) (fig. 1). In our study, we evaluate the first and the second foot-off time of the stance leg.

**Anthropomorphic parameters.** The anthropomorphic parameters are estimated from the anthropomorphic table presented in Winter (2005), using each subject's height and mass.

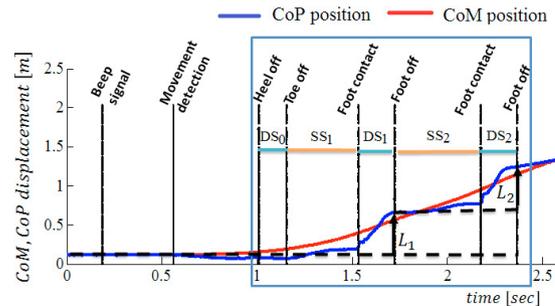


Fig. 1. Antero-posterior CoP displacement, measurement of the step positions ( $X_f = [L_1 \ L_2]$ ) from the time-course of the antero-posterior CoP displacement along with the gait cycle: three double support where both feet are on the ground ( $DS_0$ ,  $DS_1$ ,  $DS_2$ ) and two single support where one foot is on the ground ( $SS_1$ ,  $SS_2$ ).

## 3. HUMAN WALKING: A NONLINEAR OPTIMAL CONTROL MODELING

In this section, the human body modeling consists in a nonlinear optimization problem where the decision variables consisting in the walking motion parameters are optimal with respect to the known optimality criteria.

### 3.1 Decision variables

In our proposed direct optimal control (DOC) formulation the vector of decision variables  $u \in \mathbb{R}^{m+7}$  is composed of

- the **CoM smooth jerk curve**  $\ddot{c} \in \mathbb{R}^m$ , where  $m = N_{DS_0} + \dots + N_{DS_2}$ , and  $N = [N_{DS_0} \dots N_{DS_2}] \in \mathbb{R}^5$  is the vector of number of samples in each of the five gait cycle phases,
- the **step positions**  $X_f \in \mathbb{R}^2$ ,
- and the **vector of sampling time interval values**  $T_p = [T_{p_{DS_0}} \dots T_{p_{DS_2}}] \in \mathbb{R}^5$  corresponding to each gait cycle phase, as defined in Fig. 1.

The total duration of the two steps  $D = T_p^\top N \in \mathbb{R}^1$  is calculated by using the sampling size vector  $N \in \mathbb{R}^5$  which is defined in advance for each gait cycle phase and the  $T_p \in \mathbb{R}^5$  vector of sampling time values which is estimated by the DOC formulation.

### 3.2 The cost function

The basis of criteria is composed of optimality criteria proposed in Aftab et al. (2012), to which we add the minimization of each step length and the total step duration to obtain larger and faster steps. Therefore, the minimization of CoM smooth jerk curve is necessary to generate stable motions, but also it was showed that a weakly weighted minimization helps smoothing the contact forces and therefore the resulting motion. The minimization of the CoM velocity always allow quicker steps.

Let's define diagonal matrix  $\Theta \in \mathbb{R}^{m \times m}$  which diagonal is vector  $\tau \in \mathbb{R}^m$  defined by

$$\tau = [T_{p_{DS_0}} 1_{DS_0}, T_{p_{SS_1}} 1_{SS_1}, T_{p_{DS_1}} 1_{DS_1}, T_{p_{SS_2}} 1_{SS_2}, T_{p_{DS_2}} 1_{DS_2}],$$

where  $1_{DS_0}$  to  $1_{DS_2}$  are some vectors composed of as many 1 values as the dimension of each gait cycle phase  $DS_0$  to  $DS_2$ , and  $T_{p_{DS_0}}$  to  $T_{p_{DS_2}}$  are scalars that correspond to the sampling time interval value of each gait cycle phase as described above.

Table 1. Basis of criteria.

NAME	FORMULA
CoM jerk (J)	$J = \ddot{c}^\top \Theta \ddot{c}$
CoM velocity (V)	$V = \dot{c}^\top \Theta \dot{c}$
CoM acceleration (A)	$A = \ddot{c}^\top \Theta \ddot{c}$
CoP tracking (P)	$P = (p - p_{ref})^\top \Theta (p - p_{ref})$
Total duration (D)	$D = T_p^\top N$
First step position (1S)	$1S = X_f(1)^2$
Second step position (2S)	$2S = X_f(2)^2$

### 3.3 The kinematic and the dynamic constraints

**CoP.** The static balance is ensured if the CoP always stays within the base of support during the single support (SS) and double support (DS) phases while walking. Hence, this constraint is represented in the optimization problem for the SS and DS phases by:

$$-a \leq p - X_f \leq l_f - a \quad (1)$$

where  $a$  is the ankle to heel horizontal distance and  $l_f$  represents the foot length.

**CoM position and velocity.** During the optimization problem the CoM position, velocity, acceleration and jerk values at initial time  $t_0$  and final one  $t_f$  are required to be equal with the observed ones, to assure initial and final feasible values:

$$\begin{cases} (c(t_0) = c_{data}(t_0)) \wedge (c(t_f) = c_{data}(t_f)) \\ (\dot{c}(t_0) = \dot{c}_{data}(t_0)) \wedge (\dot{c}(t_f) = \dot{c}_{data}(t_f)) \\ (\ddot{c}(t_0) = \ddot{c}_{data}(t_0)) \wedge (\ddot{c}(t_f) = \ddot{c}_{data}(t_f)) \end{cases} \quad (2)$$

**Foot step placements.** To ensure feasible step placements generated by our optimization algorithm, the position of the next foot step depending on the current position of the foot in the air is bounded:

$$-B \leq X_f(i) - X_f(i-1) \leq B, \quad (3)$$

where  $B = (t_{touchdown}(i) - t_{touchdown}(i-1))v_{max}$ , with  $X_f(i)$ , the position of the next foot step on x axis,  $X_f(i-1)$  the current position of the foot in the air on x axis,  $v_{max}$  a vector of approximate maximum Cartesian speed and  $t_{touchdown}$  the time when the foot in the air is planned to touch the ground.

### 3.4 Our DOC scheme with predicted step positions and phase durations

Now, we can express the minimization problem, corresponding to the 2D gait model (where the CoM position on z-axis is considered constant and dependent on subject's height) with predicted step positions and phase durations, in the corresponding nonlinear optimization problem to be solved:

$$\begin{aligned} & \underset{u}{\text{minimize}} && \sum_{i=1}^k \alpha_i \Phi_i(u) \\ & \text{subject to} && h(u) \equiv (2) \\ & && g(u) \equiv (3) \wedge (1) \end{aligned} \quad (4)$$

where  $\alpha_i$  are positive weights corresponding to each criterion from the predefined basis  $\Phi$ ;  $k$  represents the number of proposed criteria and  $u = (\ddot{c} X_f T_p)$  is the vector of decision variables as presented in Subsect. 3.1.

In summary, the DOC scheme writes: *Find the CoM smooth jerk curve ( $\ddot{c} \in \mathbb{R}^m$ ) in x-axes, the foot step positions ( $X_f \in \mathbb{R}^2$ ) and each gait cycle phase sampling time values ( $T_p \in \mathbb{R}^5$ ) with given sampling size on each gait cycle phase ( $N \in \mathbb{R}^5$ ) by minimizing a given composite criteria (4) while maintaining balance (1), ensuring feasible step placements (3) and feasible final CoM position, velocity and acceleration values (2).*

## 4. HUMAN WALKING : AN INVERSE OPTIMAL CONTROL FRAMEWORK

The DOC scheme proposed in the previous section will be used at the core of the IOC problem which is based on the inverse KKT approach. More details about this approach can be found in Aghasadeghi and Bretl (2014), Panchea (2015), Panchea and Ramdani (2015) or Lin et al. (2016). The IOC problem aims to impute the optimality criterion (the IOC decision variables) underlying observed actual motions (the IOC known variables).

The DOC problem (4) is used to underlie the KKT optimality conditions with the decision variables composed of the optimality criteria weight values  $\alpha_i$  and known variables  $u$  :

$$\sum_{i=1}^k \alpha_i \nabla \Phi_i(u) + \sum_{i_1=1}^{m_1} \nu_{i_1} \nabla h_{i_1}(u) + \sum_{i_2=1}^{m_2} \lambda_{i_2} \nabla g_{i_2}(u) = 0 \quad (5)$$

$$h_{i_1}(u) = 0, \quad i_1 = 1 \dots m_1 \quad (6)$$

$$g_{i_2}(u) \leq 0, \quad i_2 = 1 \dots m_2 \quad (7)$$

$$\lambda_{i_2} \geq 0, \quad \lambda g_{i_2}(u) = 0, \quad i_2 = 1 \dots m_2 \quad (8)$$

where  $\nabla$  is the gradient w.r.t  $u$ ,  $m_1$  and  $m_2$  represent the number of equality and inequality constraints respectively; where conditions (6)-(7) are the primal feasibility conditions, (8) is the complementarity slackness conditions,

while (5) is the stationarity condition. The complementary slackness condition (8) implies that the  $i^{\text{th}}$  dual optimal multiplier related to the inequality constraint is zero unless the  $i^{\text{th}}$  equality constraint is active at the optimum:

$$((\lambda_{i_2} > 0 \implies g_{i_2}(u) = 0) \wedge (g_{i_2}(u) < 0 \implies \lambda_{i_2} = 0)). \quad (9)$$

The inequality constraints were found negative while testing them with experimental data, thereby based on (9) all the dual optimal multipliers are equal to zero. Therefore, the IOC problem boils down to the minimization of the residuals on (5) without the inequality constraints, while (6)-(7) are only checked to be sure that we are dealing with feasible human motions:

$$\begin{aligned} & \text{minimize} && \|A_0 z_0\|^2 \\ & z_0 = [\alpha, \nu] \in \mathbb{R}^{k+m_1} \\ & \text{subject to} && \alpha_i \geq 0 \end{aligned} \quad (10)$$

with  $A_0 = \sum_{i=1}^k \alpha_i \nabla \Phi_i(u) + \sum_{i_1=1}^{m_1} \nu_{i_1} \nabla h_{i_1}(u)$ .

Solving (10) assumes that the trajectories are only approximately optimal rather than optimal. Formulation (10) emphasizes that the IOC problems are ill-posed. When matrix  $A_0$  is not singular, trivial solutions arise. For instance,  $z_0 = 0$  is clearly solution. Furthermore, if a given composite cost function  $f$  is a solution, so do  $G \circ f$  or  $f + \kappa$ , where  $G$  is any convex increasing function and  $\kappa$  any constant. In the literature, the ill-posedness issue is solved by means of normalization methods. One can find different methods of normalization to enforce non-singular solutions:

- (1)  $\sum_{i=1}^k \alpha_i = 1$ , as in Albrecht et al. (2011) for a bi-level approach, which we denote as the *sum normalization method*.
- (2) By using some prior knowledge on the sought cost function, i.e. one of the weights is arbitrary fixed to 1 (Mombaur et al. (2010), Aghasadeghi and Bretl (2014)).
- (3) By improving the second normalization method and using each cost function as a *pivot*, thereby testing each criterion (Panchea (2015)), which we denote as the *pivot normalization method*.

In this study, the first and third ways of normalization are tested and we expect to obtain as result the same combination of criteria.

The criteria weight values are imputed by solving one least square problem (LS) with the use of the *sum normalization method*:

$$\begin{aligned} & \text{minimize} && \|A_0 z\|^2 \\ & z = [\alpha_i, \nu] \in \mathbb{R}^{k+m_1} \\ & \text{subject to} && (\alpha_i \geq 0) \wedge \left( \sum_{i=1}^k \alpha_i = 1 \right) \end{aligned} \quad (11)$$

and as many LS problems as criteria defined in the basis of criteria with the use of the *pivot normalization method*, where each criterion will be used as pivot once at a time:

$$\begin{aligned} & \text{minimize} && \|Az - b\|^2 \\ & z = [\alpha_i, \nu] \in \mathbb{R}^{(k-1)+m_1} \\ & \text{subject to} && \alpha_i \geq 0 \end{aligned} \quad (12)$$

with  $A = \sum_{i=1}^{k-1} \alpha_i \nabla \Phi_i(u) + \sum_{i_1=1}^{m_1} \nu_{i_1} \nabla h_{i_1}(u)$  and  $b = -\nabla \Phi_{i^*}(u)$  which corresponds to the gradient of the criterion used as pivot and with weight value equal to 1, i.e.  $\alpha_{i^*} = 1$ .

For the analyzed human walking task we solve eight LS problems: one as in (11) and the rest of seven as in (12). All constrained LS problems are solved with the interior-point method, while the gradients are calculated numerically. As we supposed the system's states are near-optimal, an important indicator regarding the proximity of the solution to optimality is used and corresponds to the residual norm value, denoted RN, of the LS problem: equal to  $\|A_0 z\|^2$  for (11) and to  $\|Az - b\|^2$  for (12).

By working with human actual data we do not have access to the ground truth of the criteria weight values, thereby a RN threshold is selected small enough to indicate the near-optimal hypothesis. The results which exhibit RN below or equal a chosen RN threshold value (equal to  $10^{-3}$ ) are considered sufficiently close to the optimality. Moreover, the results which exhibited RN below or equal the RN threshold value are used to solve the DOC problem as in (4) in order to estimate CoP position and to calculate the correlation values, denoted  $R^2$  between the estimated curves and the real ones.

## 5. EXPERIMENTAL DATA RESULTS

In this section, criteria defined in Table 1 are imputed from human walking motions collected as described in Sect.2. First, in Subsect. 5.1 the exhibited results for one subject (denoted as typical subject) are presented in more details. Second, Subsect. 5.2 summarizes the results which are similar for the typical subject, for the 200 trials collected for ten subjects while performing the NGC and FGC.

### 5.1 Typical subject

For the typical subject our IOC-walking approach discarded 4 out of 8 LS solutions due to large RN value, while through the accepted ones, three criteria (among the ones in the basis of criteria given in Table 1) were obtained: V, A and D. Both pivot normalization method and sum normalization method exhibited these criteria, as it can be seen in Table 2.

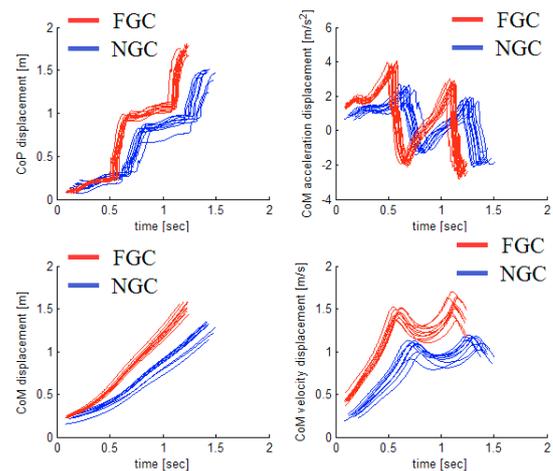


Fig. 2. Typical subject: FGC/NGC trials representation used for analyses.

Moreover, the exhibited criteria weight values are almost similar for the analyzed trials, as the standard deviation

Table 2. Results for the typical subject: mean  $\pm$  standard deviation on the optimality criteria weight values exhibited for 10 trials for NGC and 10 trials for FGC, respectively.

NGC	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_5$	$\alpha_6$	$\alpha_7$	mean(RN)
Pivot normalization method								
V	0	1	0.07 $\pm$ 0.02	0	0.82 $\pm$ 0.08	0	0	2.5 $\times$ 10 <sup>-6</sup>
A	0	16.61 $\pm$ 4.41	1	0	13.58 $\pm$ 3.78	0	0	3.4 $\times$ 10 <sup>-5</sup>
D	0	1.25 $\pm$ 0.13	0.09 $\pm$ 0.03	0	1	0	0	3.2 $\times$ 10 <sup>-6</sup>
Sum normalization method								
sum	0	0.53 $\pm$ 0.02	0.04 $\pm$ 0.01	0	0.43 $\pm$ 0.03	0	0	1.3 $\times$ 10 <sup>-6</sup>
FGC	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_5$	$\alpha_6$	$\alpha_7$	mean(RN)
Pivot normalization method								
V	0	1	0.07 $\pm$ 0.02	0	0.87 $\pm$ 0.13	0	0	1.03 $\times$ 10 <sup>-4</sup>
A	0	17.42 $\pm$ 4.29	1	0	15.6 $\pm$ 5.24	0	0	10 <sup>-4</sup>
D	0	1.21 $\pm$ 0.15	0.09 $\pm$ 0.03	0	1	0	0	7.3 $\times$ 10 <sup>-5</sup>
Sum normalization method								
sum	0	0.4 $\pm$ 0.02	0.04 $\pm$ 0.02	0	0.56 $\pm$ 0.03	0	0	4.6 $\times$ 10 <sup>-5</sup>

Table 3. Results for the ten subjects: mean  $\pm$  standard deviation on the optimality criteria weight values exhibited for 100 trials for NGC and 100 trials for FGC.

NGC	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_5$	$\alpha_6$	$\alpha_7$	mean(RN)
Pivot normalization method								
V	0	1	0.08 $\pm$ 0.01	0	0.52 $\pm$ 0.02	0	0	7.2 $\times$ 10 <sup>-5</sup>
A	0	10.14 $\pm$ 0.56	1	0	5.93 $\pm$ 0.42	0	0	6.4 $\times$ 10 <sup>-4</sup>
D	0	1.8 $\pm$ 0.07	0.2 $\pm$ 0.02	0	1	0	0	4 $\times$ 10 <sup>-5</sup>
Sum normalization method								
sum	0	0.6 $\pm$ 0.01	0.06 $\pm$ 0.004	0	0.34 $\pm$ 0.01	0	0	5.1 $\times$ 10 <sup>-5</sup>
FGC	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_5$	$\alpha_6$	$\alpha_7$	mean(RN)
Pivot normalization method								
V	0	1	0.07 $\pm$ 0.001	0	0.6 $\pm$ 0.05	0	0	1.4 $\times$ 10 <sup>-5</sup>
A	0	13.78 $\pm$ 2.22	1	0	11.75 $\pm$ 3.48	0	0	4 $\times$ 10 <sup>-4</sup>
D	0	1.7 $\pm$ 0.09	0.18 $\pm$ 0.02	0	1	0	0	9.1 $\times$ 10 <sup>-5</sup>
Sum normalization method								
sum	0	0.4 $\pm$ 0.002	0.01 $\pm$ 0.001	0	0.59 $\pm$ 0.003	0	0	4.8 $\times$ 10 <sup>-5</sup>

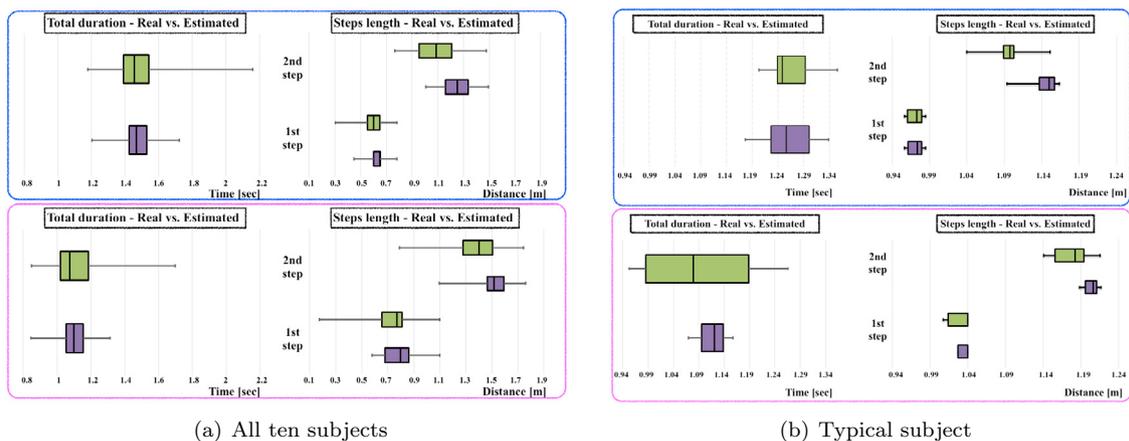


Fig. 3. Standardized representation of the distribution of real (purple) step lengths (on the right side) and total duration (on the left side) against the estimated (green) step positions and total duration. (NGC: blue; FGC: magenta)

(std) stands as proof in Table 2. The latter statement can be seen even before applying the IOC approach by calculating the correlation values between the subject's trials for NGC and FGC. These values which are between [0.9831, 1] for NGC and [0.9468, 1] for FGC clearly show that the trials are strongly correlated. Nevertheless, the V and D criteria weight values have a significant change: the V weight values decrease from NGC to FGC while the

D weight values increase as it can be seen in Table 2 and represented on Fig. 2, while the A weight were found with small values. This behaviour is not surprising as the representation of all subject's trials for both conditions in Fig. 2 suggested it even before applying our IOC approach. Fig. 2 indicates that the subject walks slowly while performing the NGC which is the opposite while performing the FGC. The minimal (min) and maximal (max) correlation values

obtained between the measured CoM/CoP positions and the estimated ones: (NGC) [0.97, 0.99] for CoP; [0.91, 0.99] for CoM and (FGC) [0.98, 0.99] for CoP; [0.88, 0.99] for CoM, clearly indicates that the measured positions fit well the real ones.

## 5.2 All subjects

When analyzing all ten subjects 100 trials per gait condition, the obtained results were found similar to the ones exhibited by the typical subject: **(a)** same exhibited three criteria: V, A and D; **(b)** in each of the analyzed gait condition the V, A and D weight values were found with a non-significant value variation for all subjects as the std stands for proof in Table 3; **(c)** all 100 per gait condition trials are strongly correlated, found with correlation values between [0.9536, 1] for NGC and between [0.9289, 1] for FGC; **(d)** V weight values decrease from the NGC to FGC, D weight values increase from the NGC to FGC and the A weight are found with small values.

The estimated CoP/CoM positions fit well the measured ones, with min and max correlation values as follows: (NGC) [0.89, 0.99] for CoP; [0.79, 0.99] for CoM; (FGC) [0.6, 0.99] for CoP; [0.65, 0.99] for CoM. Moreover, the estimated step positions and total duration, represented for all trials each gait condition by a box plot distribution (see Fig. 3(a)), were found acceptable compared to the real ones. Analyzing ten subjects had the advantage observing different behaviours while performing both gait conditions, behaviours which were pointed out by our proposed scheme through the criteria values.

## 6. CONCLUSION

This study shows that a simplified walking modeling along with an IOC approach can be an efficient scheme to bring answers to the human walking behaviour. The results clearly show that the proposed scheme can easily distinguish between natural and fast walking, while obtaining a good estimation on gait parameters.

In future work, we intend to use the proposed approach as a tool to distinguish and find invariants in subjects which have locomotion degenerative diseases. Moreover, our proposed IOC walking approach can be used in humanoid robots control where the selection of the optimality criteria weight values are made automatically and not randomly or selected by the user as it is the case in the literature.

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