A Learning-based Approach to the Real-time Estimation of the Feet Ground Reaction Forces and Centres of Pressure in Humans

Marta Lorenzini[1,2], Wansoo Kim[1], Elena De Momi[2] and Arash Ajoudani[1]
[1]*HRI² Lab, Department of Advanced Robotics, Istituto Italiano di Tecnologia, Genoa, Italy*
[2]*Department of Electronics, Information and Bioengineering, Politecnico di Milano, Milano, Italy*

***Abstract*—The feet centres of pressure (CoP) and ground reaction forces (GRF) constitute essential information in the analysis of human motion. Such variables are representative of the human dynamic behaviours, in particular when interactions with the external world are in place. Accordingly, in this paper we propose a novel approach for the real-time estimation of the human feet CoP and GRFs, using the whole-body CoP and the human body configuration. The method combines a simplified geometrical model of the whole-body CoP and a learning technique. Firstly, a statically equivalent serial chain (SESC) model which enables the whole-body CoP estimation is identified. Then, the estimated whole-body CoP and the simplified body pose information are used for the training and validation of the learning technique. The proposed feet CoP model is first validated experimentally in five subjects. Then, its real-time efficacy is assessed using dynamic data streamed on-line for one selected subject.**

***Keywords*—Human modelling, real-time estimation, learning technique.**

I. Introduction

Among the key factors accounted in human motion analysis, the knowledge of feet centres of pressure (CoP) and ground reaction forces (GRF) is crucially important. The feet CoP can be for example employed in gait analysis or for postural stability assessment. On the other hand, the GRFs are representative input data for the application of the inverse dynamics technique and can improve dynamic consistency in simulations on musculoskeletal models [1]. The direct measurement of these variables can be achieved by means of force sensors, e.g. force platforms or foot insole sensor systems, but using these devices may impose several restrictions and in certain condition such as slope walking, stair climbing or track running it is difficult to obtain good results [2]. For this reason, the interest toward approaches for the estimation of the human feet CoP and GRFs is significantly growing. One potential application for this kind of approach could be the extension of the human-robot collaboration framework presented in our previous work [3], whose aim was to monitor and prevent in real-time excessive loadings in human joints during a human-robot collaborative tasks. The proposed technique was based on the real-time estimation of the translational displacement of the whole body CoP in the presence of external forces, used along with the GRF vectors to compute the overloading joint torques throughout the task execution. This information was then used to implement a robot assistance framework to make human achieve more ergonomic body configurations.

To construct and identify the real-time CoP model employed in the procedure we used the statically equivalent serial chain (SESC) technique [4] along with the body pose measurements collected by means of a motion-capture system. Since this method allows solely to obtain the whole body CoP, the technique proposed in [3] can currently be applied to human biomechanical models represented by planar serial chains that include just one GRF. The development of this reduced model to a three dimensional (3D) one including both legs and thus the contact forces exchanged by both feet with the ground, would lead to a less rough approximation of the human body and broaden the applications of the technique to more realistic and complex 3D tasks.

Accordingly, the aim of this paper is to propose a novel approach to estimate the feet CoP and GRFs, during double support, on the basis of the whole body CoP and the total GRF. After collecting sets of measurements of the human whole body pose along with CoP and GRFs upon a large number of static postures through external sensory systems, we firstly identify the unknown body segment inertial parameters (BSIPs) of the human body to develop a whole-body CoP model with the SESC technique. Secondly, we design and train a feed-forward artificial neural network (ANN) to estimate the CoP and GRFs for the feet. The proposed method is evaluated experimentally on five subject. Then, its real-time applicability is assessed using dynamic data from a selected subject demonstrating that the human feet CoP model could be employed to extend the framework presented in [3].

II. Overview of the Method

In this section, we introduce our method to estimate the feet CoP and GRFs in real-time. It is a novel technique that combines a simplified geometrical model and a classical learning technique. To compute the parameters that characterize the model we employ the measurements collected with a motion-capture system and force sensors. We first identify the unknown BSIPs to estimate the whole-body CoP using the SESC technique. Next, a mapping from the whole-body CoP to feet CoP by means of the ANN is presented. This consideration is to reduce the amount of modelling uncertainty that is expected to be learnt by the ANN. Once the feet CoP model is identified and trained, it can be employed in real-time applications.

A. Geometrical Model: Whole-body Centre of Pressure

The whole-body centre of mass (CoM), $\mathbf{C}_M = [C_{Mx} \quad C_{My} \quad C_{Mz}]^T \in \mathbb{R}^3$ of any branched chain (e.g., leg, arm, etc.) can be modeled by geometric parameters (i.e. CoM, mass and length of each link) of the original whole-body structure using the SESC technique [4]

$$\mathbf{C}_M = \mathbf{x}_0 + \mathbf{B}\boldsymbol{\Phi}, \tag{1}$$

where matrix $\mathbf{B} = \begin{bmatrix}\mathbf{A}_0 & \cdots & \mathbf{A}_n\end{bmatrix} \in \mathbb{R}^{3\times3(n+1)}$ contains i-th link rotation matrices $\mathbf{A}_i \in SO(3)$ with respect to Σ_W. Matrix $\boldsymbol{\Phi} = \begin{bmatrix}\boldsymbol{\phi}_0^T & \cdots & \boldsymbol{\phi}_n^T\end{bmatrix}^T \in \mathbb{R}^{3(n+1)}$ includes the vector of SESC parameters $\boldsymbol{\phi}_i \in \mathbb{R}^3$, which refers to mass distribution of the human model.

To identify the unknown parameters, the whole-body CoP can be written in regressor form as

$${}^0\mathbf{C}_M = \mathbf{C}_M - \mathbf{x}_0 = \mathbf{B}\boldsymbol{\Phi}, \tag{2}$$

where ${}^0\mathbf{C}_M$ is the CoM represented in Σ_0. The regression matrix $\mathbf{B}$ and the parameter vector $\boldsymbol{\Phi}$ contain all the known and unknown parameters of the SESC.

The identification of the parameter vector $\boldsymbol{\Phi}$ in such a form can be considered as a classical least-squares problem. The rotation matrix $\mathbf{B}$ and the human base frame vector $\mathbf{x}_0$ can be calculated from the measurements collected by means of the motion-capture system. On the other hand, the CoM vector cannot be obtained directly from a sensory system. It is possible, though, to achieve the ground-projected CoM, which corresponds to the CoP in the static condition. The whole-body CoP vector $\mathbf{C}_P = [C_{Px} \quad C_{Py}]^T \in \mathbb{R}^2$ with respect to the Σ_W can thus be calculated using force sensors (i.e. force platforms or an insole sensor system) as

$$\mathbf{C}_P = \frac{\mathbf{f}_L \cdot \mathbf{C}_{P,L} + \mathbf{f}_R \cdot \mathbf{C}_{P,R}}{\mathbf{f}_L + \mathbf{f}_R}, \tag{3}$$

where, $\mathbf{f}_L$ and $\mathbf{f}_R$ are the GRF of left and right foot, respectively. The CoP of each foot $\mathbf{C}_{P,L}$ and $\mathbf{C}_{P,R}$ with respect to the Σ_W calculated as follows

$$\mathbf{C}_{P,L} = \mathbf{x}_L^* + \mathbf{A}_L^{*\,LI}\mathbf{C}_{P,L}$$

and

$$\mathbf{C}_{P,R} = \mathbf{x}_R^* + \mathbf{A}_R^{*\,RI}\mathbf{C}_{P,R}. \tag{4}$$

The superscript $(.)^*$ above symbolises the pre-multiplication of the projection to the x-y ground plane. The position of the feet $\mathbf{x}_L^*$ and $\mathbf{x}_R^* \in \mathbb{R}^2$, and the corresponding orientations $\mathbf{A}_L^*$ and $\mathbf{A}_R^* \in \mathbb{R}^{2\times2}$ are measured from the motion-capture system. ${}^{LI}\mathbf{C}_{P,L}$ and ${}^{RI}\mathbf{C}_{P,R}$ correspond to the measured CoP value with respect to the force sensor frame on left and right, respectively. Accordingly, the least-squares problem can be solved by the stacked matrices for p pose set of $\mathbf{B}^*$ and ${}^0\mathbf{C}_P$ as $\mathbf{W} \in \mathbb{R}^{2p\times3(n+1)}$ and $\boldsymbol{\Omega} \in \mathbb{R}^{2p\times1}$, respectively. The vector of the identified SESC parameters $\hat{\boldsymbol{\Phi}} \in \mathbb{R}^{3(n+1)}$ can be calculated as

$$\hat{\boldsymbol{\Phi}} = \mathbf{W}^+\boldsymbol{\Omega}, \tag{5}$$

Fig. 1: The selected wearable sensor systems: a motion-capture suit and insole sensors.

where $\mathbf{W}^+ = \left(\mathbf{W}^T\mathbf{W}\right)^{-1}\mathbf{W}^T$ is the Moore-Penrose generalised inverse. In the static condition we can compute the CoP by projecting onto the x-y plane the whole-body CoM estimated by (1) with the identified SESC parameters (5).

B. Learning Technique: Feet Centres of Pressure

To estimate the feet CoP and successively compute the feet GRFs, we employ the multi-layer ANN technique, using as inputs the whole-body CoP estimated by the simplified SESC model and body configurations measured with the motion-capture system. Supporting this choice, it has been shown that supervised multi-layer ANN with the proper input data and a non-linear activation function are capable of representing accurate approximations and mappings [5]. Specifically, a feed-forward ANN with one hidden layer and enough number of neurons in hidden layers, can fit any finite input-output mapping problem [6].

The training of the ANN model for each subject is performed in the off-line phase so as to build real-time model. To achieve the best possible results, different combinations of the training functions, numbers of neurons in the hidden layer and sets of input data are tested. As regards the input data, the whole-body $\hat{\mathbf{C}}_P$ from the SESC model, the orientation matrix of the simplified human model $\mathbf{B}$ and the pelvis, the left foot and the right foot positions are ultimately employed for the training and the validation. As regards the structure, we build a feed-forward ANN composed by one hidden layer containing four neurons with a non-linear activation function and an output layer with a linear function. The network is trained with the target data (e.g. the measured feet CoP using the force sensors) using the weights and bias values according to Levenberg-Marquardt optimisation.

Consequently, the feet CoP $\hat{\mathbf{C}}_{P,R}$ and $\hat{\mathbf{C}}_{P,L}$ can be estimated in real-time. In addition, deriving from (3), we can obtain the distribution gain ζ for each foot as

$$\begin{bmatrix}\zeta_L & \zeta_R\end{bmatrix} = \begin{bmatrix}\left|\frac{\hat{\mathbf{C}}_P - \hat{\mathbf{C}}_{P,R}}{\hat{\mathbf{C}}_{P,L} - \hat{\mathbf{C}}_{P,R}}\right| & \left|\frac{\hat{\mathbf{C}}_P - \hat{\mathbf{C}}_{P,L}}{\hat{\mathbf{C}}_{P,R} - \hat{\mathbf{C}}_{P,L}}\right|\end{bmatrix}. \tag{6}$$

Using these distribution gains, even feet GRF can be easily computed from the overall GRF.

III. Verification of the Method

This section first provides the performance evaluation of the proposed method. Then its real-time applicability is assessed with dynamic data during an on-line session. We will focus on the results for the estimation of the feet CoP since it is more meaningful for our purposes but even feet GRF, as previously said, can be computed.

A. Model Identification and Validation

Five healthy male volunteers (age: 28.6 ± 4.3 years; mass: 84.7 ± 10.7 kg; height: 182.2 ± 2.9 cm) [1] were recruited in the experimental session. A written informative consent was obtained after explaining the experimental procedure. The sensory systems employed in our experimental setup, illustrated in Fig. 1, are wearable and light-weight so as they do not add additional constraints on the human mobility. The measurement of the whole-body human motion is achieved using a wearable MVN Biomech suit (Xsens Technologies) provided with seventeen inter-connected inertial measurement unit (IMU) sensors. On the other hand, the calculation of the CoP and the measurement of the vertical GRF (vGRF) are performed using OpenGo insole sensors (Moticon GmbH). Each subject was asked to wear the MVN Biomech suit and the OpenGo insole sensors and then required to hold 200 static poses for the data collection. During the acquisition, the postures were chosen by each subject arbitrarily but with the requirement to change the orientations of each segment and the position of the feet CoP as much as possible in between, to obtain variables as linearly-independent as possible. The large amount of postures collected along with their variability are necessary to build a suitable set of input data for the parameters identification of the proposed synergistic model.

The SESC parameters identification was done using 80 selected static poses that were considered suitable given the level of approximation of our human model (details can be found in [4]). Table I presents the means and the standard errors of the position error of the CoP with respect to the Σ_W to evaluate the performance of the SESC technique. This position error was computed in x-direction and in y-direction for all the 200 postures performed by five subjects. We compared $\mathbf{C}_{P_{wt}}$ and $\hat{\mathbf{C}}_{P_{wo}}$ positions, computed with (3) using data measured by the OpenGo insole sensors and estimated by the SESC model, respectively. The mean position error was $1.83 \times 10^{-3} m$ in the x-direction and $1.40 \times 10^{-3} m$ in the y-direction across all postures for the subject with the worst results, providing a solid evidence on the accuracy of the on-line CoP model.

For the training of the ANN we used 160 static poses (around 80% of the whole dataset) which were in fact adopted as the training set. Table II presents the means and the standard errors of the position errors between the feet CoP measured by the OpenGo insole sensors and the estimated ones by the ANN. This errors were computed for each subject on the x-axis and on the y-axis for the left foot and for the right foot across 40 postures that were used as the validation set to examine the network performance (around the other 20% of the whole dataset). The magnitude of the error was uniform between the subjects, demonstrating that the proposed synergistic approach can deal with varying patterns of movement and human body models with different inertial parameters. The consistency of the error in the x and y directions and the level of accuracy achieved were suitable for the target applications of this work (human-robot collaboration scenarios).

B. Real-time applicability evaluation

To conduct an effective validation of the method proposed, its performance must be assessed in real-time employing dynamic data as an input. One subject (age: 30 years; mass: 76.5 kg; and height: 1.78 m) was asked to wear the MVN

[1] Subject data is reported as: mean ± standard deviation.

TABLE I: Means and standard errors of the position errors between the whole body CoP measured using the OpenGo insole sensors, and the CoP estimated by the identified SESC model. The errors are computed for each subject on the x-axis and on the y-axis across 200 postures.

Subject	CoP errors (cm)	
	$C_{P_x,L}$	$C_{P_y,L}$
1	1.34 ± 0.04	1.33 ± 0.04
2	1.57 ± 0.04	1.34 ± 0.04
3	1.45 ± 0.04	1.56 ± 0.04
4	1.76 ± 0.05	1.70 ± 0.05
5	1.83 ± 0.05	1.40 ± 0.05

TABLE II: Means and standard errors of the position errors between the CoP measured using the OpenGo insole sensors and the CoP estimated by the ANN. This errors are computed for each subject on the x-axis and on the y-axis for the left foot and for the right foot across 25 postures.

Subject	CoP errors (cm)			
	$C_{P_x,L}$	$C_{P_y,L}$	$C_{P_x,R}$	$C_{P_y,R}$
1	1.88 ± 0.09	1.25 ± 0.06	1.63 ± 0.06	2.95 ± 0.01
2	2.14 ± 0.08	1.93 ± 0.07	1.80 ± 0.06	1.57 ± 0.06
3	1.88 ± 0.06	0.57 ± 0.02	1.53 ± 0.05	1.30 ± 0.04
4	2.28 ± 0.07	0.86 ± 0.03	1.56 ± 0.04	0.75 ± 0.03
5	1.42 ± 0.05	0.53 ± 0.01	1.57 ± 0.05	0.71 ± 0.03

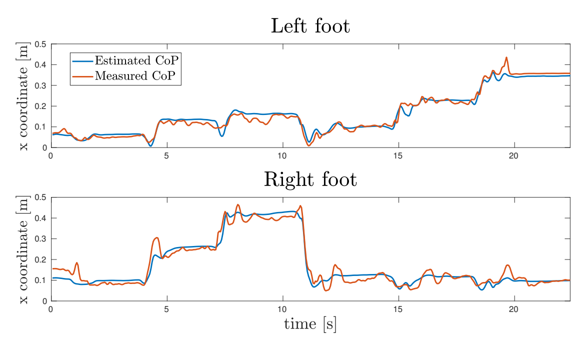

Fig. 2: X coordinate of the position of the measured (red line) and estimated (blue line) CoP for the left foot (upper chart) and for the right foot (lower chart).

Biomech suit and the OpenGo insole sensors and move in the workplace assuming different positions of the feet and thus different position of the feet CoP, changing the body configuration in between. This task was repeated for three trials. In Fig. 2 we present the results of one trial, showing the x coordinate of the CoP measured with the OpenGo insole sensors (red line) and estimated by means of the proposed method (blue line) both for the left (upper chart) and for the right (lower chart) foot. We focus on the x coordinate of the feet CoP position since the work that we want to extend [3] consider so far only task that are mainly performed along the sagittal plane. Since the estimated positions of the feet CoP are meaningfully similar to ones measured by the external sensors, we can assert that our method can deal with dynamic data streamed on-line. Moreover, the values of the means and standard deviation of the position error between the measured and estimated feet CoP computed for each trial, presented in Table III, provide a further evidence on the real-time applicability of the feet CoP model. As already mentioned, the level of accuracy achieved is suitable for the target applications of this work, namely human-robot collaboration scenarios.

TABLE III: Means and standard deviations of the position errors between the CoP measured using the OpenGo insole sensors and the CoP estimated by the synergistic model. This errors are computed for each subject on the x-axis and on the y-axis for the left foot and for the right using dynamic data collected in real-time.

Trials	CoP errors (cm)			
	$C_{P_x,L}$	$C_{P_y,L}$	$C_{P_x,R}$	$C_{P_y,R}$
1	1.47 ± 1.15	0.54 ± 0.39	2.11 ± 1.69	0.61 ± 0.41
2	1.61 ± 1.30	0.95 ± 0.47	1.76 ± 1.42	0.62 ± 0.39
3	2.13 ± 0.20	1.19 ± 0.08	3.55 ± 0.53	0.98 ± 0.09

IV. Conclusion

In this work we proposed a novel approach for the real-time estimation of the human feet CoP and GRFs from the whole body CoP and the human body configurations, using wearable and light-weight sensory systems. The method can achieve quite accurate results in static conditions and shows promising evidences for the real-time applications. As a result, using the proposed technique it will be possible to extend our previous work [3] to more realistic interaction scenarios, including the double support phase.

Future works will focus on the improvement of the accuracy and reliability of the proposed model by using dynamic data as the training set.

References

[1] R. Fluit, M. S. Andersen, S. Kolk, N. Verdonschot, and H. F. Koopman, "Prediction of ground reaction forces and moments during various activities of daily living," *Journal of biomechanics*, vol. 47, no. 10, pp. 2321–2329, 2014.

[2] Y. Jung, M. Jung, K. Lee, and S. Koo, "Ground reaction force estimation using an insole-type pressure mat and joint kinematics during walking," *Journal of biomechanics*, vol. 47, no. 11, pp. 2693–2699, 2014.

[3] W. Kim, J. Lee, L. Peternel, N. Tsagarakis, and A. Ajoudani, "Anticipatory robot assistance for the prevention of human static joint overloading in human–robot collaboration," *IEEE Robotics and Automation Letters*, vol. 3, no. 1, pp. 68–75, 2018.

[4] A. González, M. Hayashibe, V. Bonnet, and P. Fraisse, "Whole body center of mass estimation with portable sensors: Using the statically equivalent serial chain and a kinect," *Sensors*, vol. 14, no. 9, pp. 16 955–16 971, 2014.

[5] K. Hornik, "Approximation capabilities of multilayer feedforward networks," *Neural networks*, vol. 4, no. 2, pp. 251–257, 1991.

[6] S. Karsoliya, "Approximating number of hidden layer neurons in multiple hidden layer bpnn architecture," *International Journal of Engineering Trends and Technology*, vol. 3, no. 6, pp. 714–717, 2012.