2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Towards balance assessment using Openpose

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***Abstract*—The ability to assess balance is essential to determine a patients ability to mitigate any risk of falling. While current assessment tools exist, they either have limitations in that there is no quantitative data recorded, or that they are impractical for general use in clinical settings. In this work, we aim at assessing balance using single-camera videos. In particular, the proposed method uses OpenPose to calculate the Center of Mass and Center of Pressure trajectories. To determine the validity of this approach, estimates obtained in an experimental study were compared to recordings obtained through the use of 3D motion capture and force plate. Our results indicate that this inexpensive, easy to use, and portable alternative has the potential to act as a suitable replacement to assess balance in clinical settings.**

***Index Terms*—Balance assessment, Center of pressure, Markerless motion capture, Openpose**

I. Introduction

Past infanthood, balancing becomes second nature to humans, requiring little to no direct thought when performing the act of balancing. However in reality, balance control is a complex process involving the coordinated action of biomechanical, sensory, motor and central nervous system components. These control strategies result premarily in the action of the ankle and hip joints in the anteroposterior (AP) and mediolateral (ML) planes to control standing balance. Among the variables involved in the study of balance, the Center of Mass (CoM) and the Center of Pressure (CoP) are the most used parameters, since their dynamics may represent actions required to maintain balance, for instance after perturbations [1].

Balance disorders are primarily found amongst the older population, with studies indicating a high incidence of falls in those aged over 65 years [2]. Nevertheless, problems also occur in the younger population due to multiple factors, such as physical injuries, diseases or specific neurological conditions.

Methods to evaluate balance are important to address the possible risks of falls and to mitigate fall-related injuries. Widely used protocols involve the Berg Balance Scale [3]. Among other aspects, these simple tests are popular due to their ability to assess balance without the need for specialized equipment. Nonetheless, sensor-based methods could provide further insights into subject-specific deficits or compensation strategies, while also enabling automatic computation of balance metrics. Furthermore, such systems may provide real-time feedback for rehabilitation protocols targeting balance, for instance using games [4].

Candidate measurement technologies to enable quantitative balance assessment range from conventional optical motion capture technology to wearable sensors. Considering use in clinical settings, price range and ease-of-use may favour technologies such as sensors that combine color and per-pixel depth information (i.e. RGB-D sensors, such as the Microsoft Kinect) or inertial sensors [5]. One alternative is to employ computer vision libraries used for human 2D estimation, such as OpenPose [6] and DeepLabCut [7]. In particular, Openpose has the ability to estimate 25 human key points from single-camera videos, which may then be used to compute balance-related indexes. The long-term goal in this research effort involves using this information to develop an non-invasive, fast, and portable method to assess human balance, particularly considering the ubiquity of cameras in modern society.

The use of Openpose or similar software tools for clinical applications has been proposed in previous studies, particularly for gait analysis [8], [9], [10]. To the best of our knowledge, there has been no use of markerless video-based skeleton tracking tools, such as OpenPose, to assess human balance.

In this work, the main goal is to develop a system that employs a single-camera video to estimate CoM and CoP horizontal trajectories during AP and ML sway using OpenPose. The results obtained in a pilot observational study are compared to data acquired using consolidated measurement systems, notably an optical motion capture system and a force plate.

II. Materials and Methods

A. Subjects and protocol

Three subjects (2 females and 1 male, 171 ± 13 cm, 70 ± 16 kg) without any known balance deficit were recruited for this study. The research was approved by the Ethics Committee at the University of Queensland, in accordance with the Helsinki Declaration, and all volunteers signed an informed consent form.

All subjects performed a total of four tests, two in each position (AP and ML). Participants were instructed to sway, pivoting from the ankles with minimal hip flexion and arms resting on either side of the body. They were instructed to oscillate twice to both sides until a point close to their stability limit was reached. This specific movement was chosen in this preliminary evaluation, since the relation between CoM and CoP trajectories may be a useful tool to assess balance [1].

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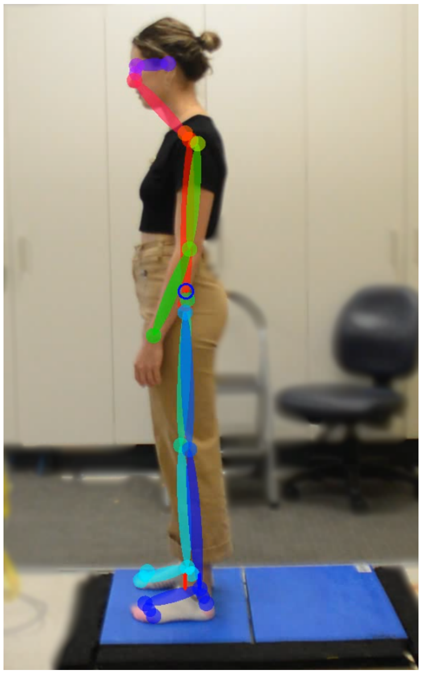

Fig. 1: OpenPose output of a participant starting AP sway. The blue circle illustrate the estimated CoM, while the red arrow near the feet depict the calculated CoP.

Movement was recorded at 120 Hz using an optical motion capture system (Optitrack Flex 13, USA) and a single force plate (Bertec 4060-07, USA). CoM estimation was based on markers placed at the left and right anterior superior iliac spine (ASIS) and posterior superior iliac spine (PSIS) positions. Simultaneously, videos were recorded for OpenPose analysis (Nikon D3200 with AF-S DX Nikkor 18-55mm f3.5-5.6G, Japan) at 60 fps. The camera was positioned orthogonally to the movement at an appropriate distance capture the movement[1]. The experimental setup is depicted in Fig. 1, along with joint estimates provided by OpenPose.

B. OpenPose data processing

Processing of OpenPose data is performed considering minimal input from the user is required. For that reason, the method includes additional steps that evaluate the integrity and quality of estimated key points. Note that for other applications, further pre-processing stages may be required, such as when multiple persons are tracked by OpenPose.

1) Occlusion of body parts: Since a single camera is only able perceive two dimensions worth of data, it is possible for certain body parts to remain obscured in the the cameras field of view. In the current protocol, this does not occur for ML trials, but in AP sway the key points of only one side of the body may be found.

Therefore before any analysis of balance was conducted, the script first compares the left and right counterparts for each limb position. If both counterparts are found then the position of the CoM is computed using Eq. 1. However, if only one of the two parts are found, it is assumed that the body remains symmetrical along the sagittal plane, hence any obscured body parts should have the same (x, y) coordinate as its visible counterpart.

2) Unit conversion: In some applications, such as [8], authors have decided to calculate measures of clinical interest based on information provided directly by OpenPose. One alternative is employing a method to allow for conversion between pixels and meters, particularly if comparison with other measurement systems is desired. Two methods have been evaluated in this work: placing an object of known length near the subject, or using as an input the subjects height. We have finally chosen the latter in order to simplify the experimental setup.

This choice has led to an additional problem, since the OpenPose model used to locate key points has a maximum height located at the nose and not the top of the head. To rectify this, an approximate offset between the top of the head is used, where the average vertical displacement between the root of the nose (selllion) to the top of the head were taken from [11] (10.77 and 10.06 cm for males and females, respectively). As both height and gender were input as parameters in the method, unit conversion may the be performed at the subjects depth in the frame.

3) Smoothing: Pilot testing has suggested that noise present in OpenPose estimates were negatively affecting the calculated CoM and CoP positions. As double differentiation is required for the computation of CoP position, the issue is accentuated in this case.

In this work, smoothing of measured data was performed using the Satvizky-Golay filter [12]. It may be seen as a weighted moving average filter which is generated by using linear least squares to fit subsets of adjacent data points with a n^{th}-order polynomial to obtain the corresponding filter coefficients.

4) Center of Mass: The CoM position is calculated using the segmentation method, where the CoM is estimated by summing the moments of masses of individual body segments. Considering the percentage of body segment weight with respect to the full body weight (obtained in [13]), the CoM position may be computed as follows:

$$CoM = \sum_{i=1}^{n} m_i CoM_i, \tag{1}$$

where CoM_i are the (x, y) coordinates of individual body segments from the top left corner of the frame, m_i refers to the percentage of each body segment weight, and n is the number of individual body segments.

As the majority of the key points in which OpenPose generates are of joint positions, there are certain body segments from [13] that may not be directly located via the OpenPose output. Instead specific combinations of key points may be utilized to interpolate an approximate

[1]There is no need to employ a fixed distance to the user, as described in Sec. II-B.

body segment position dependent on the orientation of the camera. For example, the right shank position may be approximated by averaging the positions of the right knee and right ankle. Also, within the model used in OpenPose the hand is not tracked. Both these limitations further increase errors that are inherent of the segmentation method.

5) Center of Pressure: The calculation of CoP position is based on the inverted pendulum model. In this ankle-centered model, the body experiences two forces in the vertical direction, one due to gravity going downwards applied at the CoM and a resultant force to counteract the previous force, applied at the CoP [1]. The model may be given by

$$CoP = (CoM_x - O_x) + \frac{I\alpha}{Mg}, \quad (2)$$

where CoP refers to the centre of pressure given with respect to the pendulum origin O, g refers to gravity, I is the mass moment of inertia, and α is the angular acceleration of the inverted pendulum. The total body mass M is one of the inputs required by this method.

C. Data Analysis

The results are then utilized to compute metrics used to provide a preliminary comparison between OpenPose-generated CoM and CoP with respect to estimates provided by the motion capture systems. Two metrics are used to illustrate CoM and CoP tracking errors, namely the Pearson Correlation Coefficient (r) and the Root Mean Squared Error (RMSE).

III. Results and Discussion

Tables I and II illustrate the obtained results, listing both r and RMSE computed for each trial. In addition to the tables, Figs. 2 and 3 depict sample CoM and CoP trajectories, respectively, calculated for Subject C using both measurement systems. Both figures refer to the same trial, thus depicting that the two variables are in anti-phase during sway.

Regarding estimates obtained using OpenPose, one may observe (e.g. in Fig. 2) that the horizontal displacement of the CoM is symmetric for ML sway, while not the case for the AP movement. Considering the instructions given to participants, which explicitly mentioned avoiding movement of the foot, AP sway resulted in positive displacements only for all participants.

The results outlined in Tab. I and II provide average values of 0.9928 and 1.3151 for r and $RMSE$, respectively. In this work, we have not evaluated the method performance for balance assessment. Nevertheless, we are able to discuss some limitations of the proposed method. For instance, small oscillations on CoP displacement were undetected by the OpenPose method, which may be due to the smoothing applied, but also other features (e.g. camera sampling rate, resolution). Another issue involves how OpenPose errors propagate to final estimates. For instance, it may be observed in Fig. 1 that both feet estimates are not perfectly aligned, which eventually led to errors in the upright position (e.g. Figs. 2 and 3).

TABLE I: CoM position estimated using optical motion capture data and the proposed OpenPose-based method.

Subject	Trial	ML		AP	
		r	RMSE (cm)	r	RMSE (cm)
A	1	0.9980	1.7152	0.9863	0.7637
	2	0.9990	1.1915	0.9898	0.6110
B	1	0.9984	0.7706	0.9923	1.5440
	2	0.9983	1.0665	0.9968	0.9362
C	1	0.9996	0.9479	0.9966	0.8086
	2	0.9996	0.9479	0.9928	0.8171
Average		0.9988	1.1066	0.9924	0.9134

TABLE II: CoP position estimated using a force plate and the proposed OpenPose-based method.

Subject	Trial	ML		AP	
		r	RMSE (cm)	r	RMSE (cm)
A	1	0.9941	1.8120	0.9847	1.3639
	2	0.9941	1.8120	0.9756	1.8840
B	1	0.9956	1.5283	0.9877	1.5486
	2	0.9949	1.8811	0.9881	1.2359
C	1	0.9913	1.7762	0.9901	1.1277
	2	0.9902	1.8336	0.9919	1.6386
Average		0.9934	1.7739	0.9864	1.4665

IV. Conclusions

Availability of an inexpensive and uncomplicated tool to assess balance could improve diagnosis and treatment of balance disorders. Hence, in this work we have developed a method to estimated CoM and CoP trajectories using single-camera videos. Preliminary evaluation was performed on young adults swaying on both AP and ML planes. The results obtained using the proposed method were compared to standard measurement modalities (motion capture system and force plate), and the corresponding calculated r and $RMSE$ have provided an early evidence of performance.

Future works involve both the application of methods presented here in a broader study including younger and older adults, as well as the integration of online models of oscillatory movement [14] and automatic simultaneous segmentation and quantification, both methods previously developed by the group [15].

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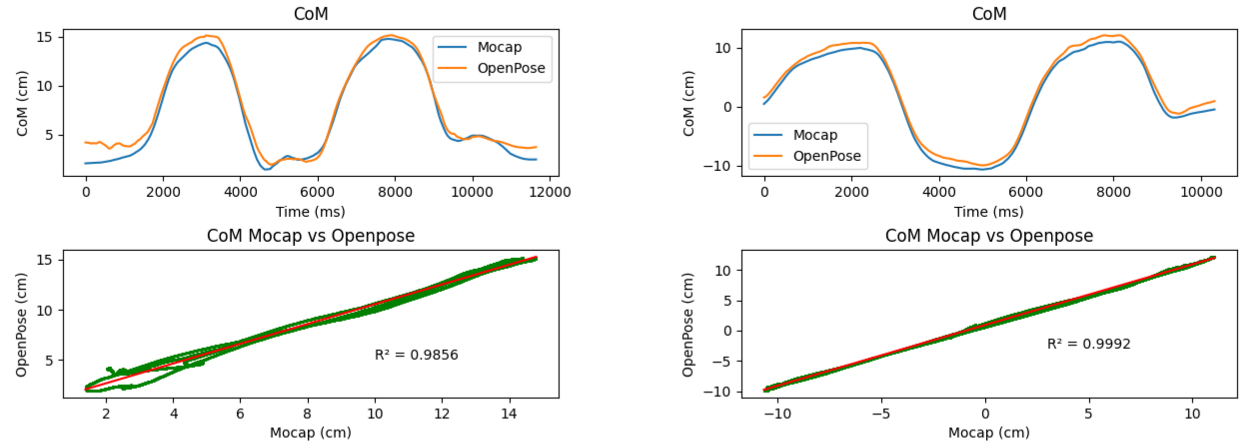
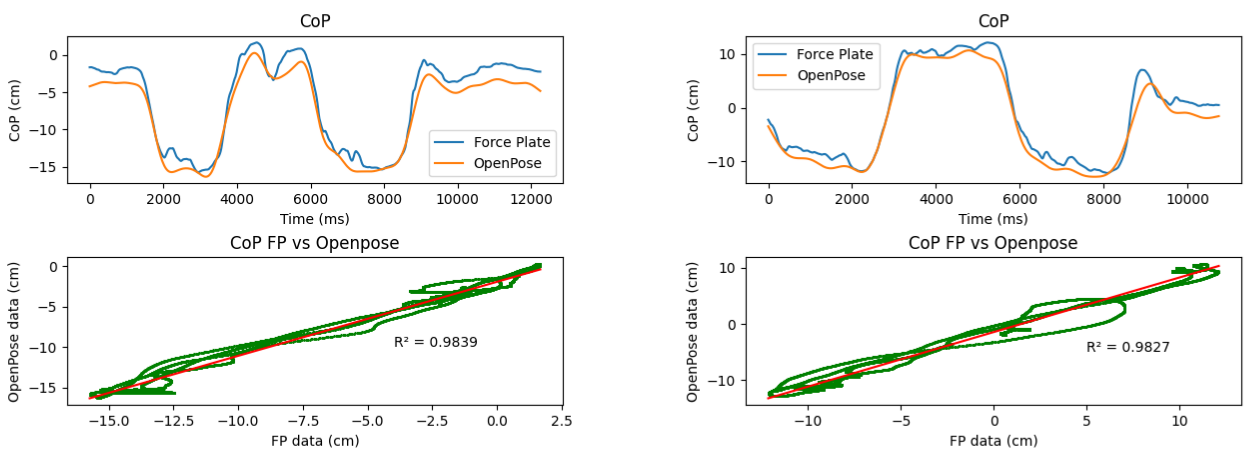


(a) (b)

Fig. 2: CoM horizontal trajectories obtained for Subject C when performing (a) AP and (b) ML sway.



(a) (b)

Fig. 3: CoP estimates obtained for Subject C when performing (a) AP and (b) ML sway.

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