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Executive Summary of the Thesis

Estimation of a climber's Centre of Mass fusing information from a sensorized climbing wall and a monocular video

Laurea Magistrale in Biomedical Engineering - Ingegneria Biomedica

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1. Introduction

The study of human motion is crucial for optimizing athletic performance and rehabilitation outcomes. Traditional methods of motion analysis, such as marker-based optical motion capture, have limitations that hinder their application in real-world contexts, can be time-consuming, uncomfortable, and restrict freedom of movement [6]. As a result, there is growing interest in developing out-of-the-lab methods for motion capture that do not require markers or sensors attached to the body and can be performed in natural and unconstrained environments. Out-of-the-lab marker-less motion capture provides a multitude of benefits that can be leveraged across diverse industries, particularly in sports and rehabilitation. In sports, sciences can support athletes in improving their performance, while in rehabilitation, an out-of-lab method can create a more enjoyable, and allow for a truthful environment for young patients.

The ACCEPT (Adaptive Climbing for Cerebral Palsy) project is an assessment of motion in this field, aiming to create an adapted, sensorized, reconfigurable, and interactive climbing wall to respond to the rehabilitation needs of children with Cerebral Palsy. Previous studies attempted to integrate a video system with the force sensors of the climbing wall, but encountered various limitations. The lack of synchronization between the two systems, coupled with the need for manual frame-by-frame tracking, prevented the extraction of three-dimensional biomechanical parameters. To overcome this limitations, a new marker-less, out-of-lab approach was developed that can accurately extract key biomechanical parameters for sport climbing analysis, with a particular focus on the Centre of Mass (CoM) that represent a critical factor in climbing, as it greatly affects the stability and balance of the climber. The approach will integrate data from ACCEPT wall that records force distribution and a neural network that detects the 2D pose of the climber from monocular video footage. The challenge of this work was to extract the 3D CoM by employing a simple setup consisting of a single camera and a sensorized wall. By combining the two data sources, the proposed method will provide a more comprehensive analysis of the climber's Center of Mass in all three dimensions.

2. Materials and Methods

To determine the 3D trajectory of the CoM on the ACCEPT wall, first a camera-based system (MCoM) was developed. MCoM was capable of calculating the 2D trajectory of the CoM, and its accuracy was evaluated by comparing it with the Center of Mass obtained from Vicon's optoelectronic system (VCoM), which is considered the gold standard. Then a second system, WCoM, was developed. WCoM used MCoM to determine the CoM's trajectory in the xy plane, which is parallel to the climbing wall, while the z-component of the trajectory was calculated using data obtained from the force sensors of the ACCEPT wall. The accuracy of WCoM in calculating the CoM's z-component was evaluated by using MCoM with a second camera placed laterally to the wall, this allowed for a comparison between the z-component trajectory data obtained from both systems and enabled aggregation of errors, which was utilized to assess the overall accuracy of the 3D CoM estimation provided by WCoM.

2.1. Centre of Mass extraction from the camera-based system (MCoM)

As previously mentioned, MCoM is a markerless method for assessing the 2D Centre of Mass that utilizes a monocular video positioned in front of the climbing wall, operating at a sample rate of 60 Hz. Mediapipe Pose, a neural network implementing a pose estimation algorithm [2], was used to extract 33 keypoint landmarks representing body segments from the video. MCoM was developed to calculate the Center of Mass using these landmarks, and the total CoM was obtained by combining the relative center of masses of each body segment (Figure 1). From the 2D pose extract from Mediapipe Pose, MCoM used a geometric model that involved a weighted average of the relative center of masses of each body segment. This weighted average was based on the Zatsiorsky anthropometric table [4].

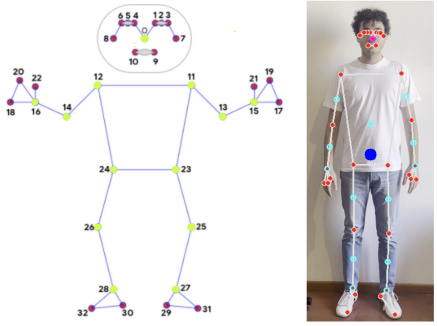


Figure 1: On the left, the Mediapipe topology displays yellow landmarks used by MCoM. On the right, small teal circles represent calculated relative centers of mass, and a large blue circle shows the subject's whole-body Center of Mass in orthostatic position.

2.1.1 Validation study MCoM

A validation study was performed against VCoM, the gold standard, which through the use of the *Plug-in Gait* protocol estimates the position of the CoM in the three directions. Static and dynamic tests were conducted to assess the accuracy of MCoM in calculating the position of the CoM and how it behaved in the presence of oscillations simulating the behavior of a climber. The validation study involved performing three tasks, namely standing, overhead squat and lateral squat, for 10 repetitions each. MCoM was used in two cameras with frontal and lateral views. Figure 2 and 3 compare MCoM with the gold standard VCoM during the overhead squat task, with the side view used to assess the accuracy in reconstructing the z-coordinate of the CoM, i.e., the distance to the wall.

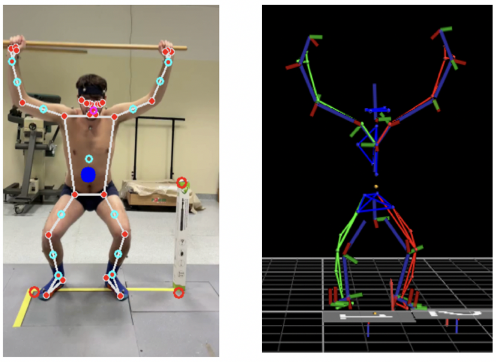


Figure 2: Front view.

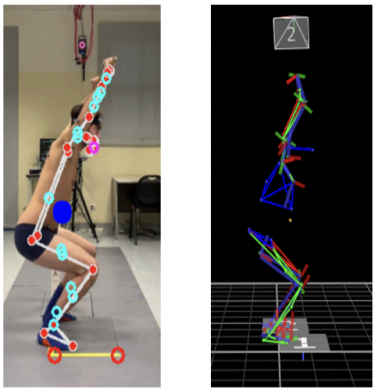
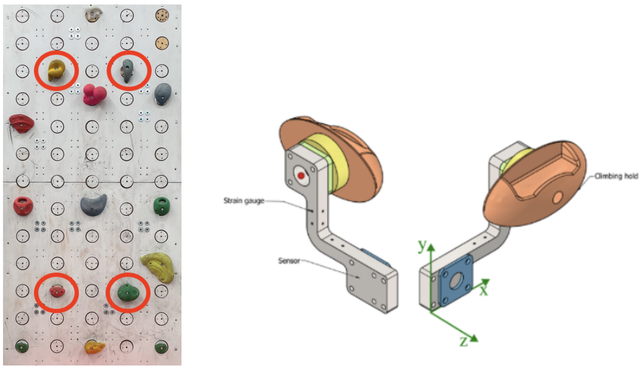


Figure 3: Lateral view.

2.2. Centre of Mass extraction from the sensorized climbing wall

ACCEPT wall measures the 3D force vector exerted on each hold without interfering with the climber's experience. It consists of holds with integrated tri-axial load cells (Figure 4b), each with a specialized data acquisition system that transmits information to a central processing unit [3]. Optimized through FEM (Finite Element Method) analysis, the sensor's shape and strain gauge placement provide 5-1600 N resolution and can withstand up to 2400 N without damage. The hold sensors were calibrated using a testing rig that featured three orthogonal planes to align with the main directions of the x, y, and z axes. To calibrate the hold sensors, a 10 Kg weight was applied and the expected value of 98.1 N was detected to ensure the accuracy of the calibration.

The wall was first used to detect the CoM during a static position by employing four sensored holds (Figure 4a). The equations proposed by Maffiodo et al. [5] were used to calculate the trajectory of the CoM. Double integration was performed by combining forces from the four holds, but as expected this resulted in drift due to additive noise. Despite the issue of drift in the trajectory, the sensorized climbing wall was still utilized to calculate the acceleration and the static z-coordinate of the CoM at each time step. These measured quantities were then incorporated into the WCoM method.



(a) The four holds being considered.

(b) The sensor hold [3].

Figure 4: Four sensorized holds used for static acquisition analysis.

2.3. 3D Centre of Mass using WCoM

The WCoM method combines data from both ACCEPT wall and the camera based-system MCoM to estimate the 3D center of mass during climbing. Two techniques have been employed to achieve this. The first approach uses MCoM to obtain the x and y components and applies a low-pass filter to the force signals for the z component estimation. The second approach involves a Kalman filter to combine information from MCoM and the sensorized wall.

2.3.1 Low Pass Filter

An elliptical low-pass filter was used to process the force signal from ACCEPT wall. This was necessary due to the quantization of the signal during data acquisition, resulting in noise and errors. The filter considered had a cut-off frequency of 0.5 Hz, chosen based on the assumption that low-frequency components were dominant.

2.3.2 Kalman Filter

The developed mathematical model for the Kalman filter assumed the CoM as a point undergoing uniformly accelerated motion, based on the first law of dynamics. The model describes the position, velocity, and acceleration of the CoM using the following equations:

$$\begin{cases} p(t+1) = p(t) + v(t)\Delta t + \frac{1}{2}a(\Delta t)^2 \\ v(t+1) = v(t) + a\Delta t \\ y(t) = [p(t), a]^T \end{cases} \tag{1}$$

where p is the position of the center of mass, v its velocity, a its acceleration, Δt the time step and $y(t)$ the vector of the measured quantities. Collecting the state ($\vec{p}$, $\vec{v}$, $\vec{a}$) of the system in the vector $x(t)$, the system 1 can be expressed as:

$$\begin{cases} x(t+1) = Ax(t) + \eta(t) \\ y(t) = Hx(t) + \mathcal{E}(t) \end{cases} \tag{2}$$

where A and H represent respectively the system and measurement matrices. White Gaussian noise with zero mean and covariance matrices Q and R are used to account for process and measurement noise, denoted by $\eta(t)$ and $\mathcal{E}(t)$, respectively [1]. The covariance matrices Q and R were calibrated to optimize the performance of the Kalman filter in estimating the trajectory of the Center of Mass.

2.3.3 Validation study WCoM

To evaluate the effectiveness of the two techniques for WCoM, a data acquisition process was conducted on the climbing wall using MCoM in two cameras placed frontally and laterally at a distance of 2.5 meters from the wall. As mentioned before the lateral view served as a benchmark for assessing the accuracy of WCoM in calculating the z coordinate. By comparing MCoM to VCoM directly as described in Section 2.1, the accuracy of the z-coordinate of WCoM could be assessed, taking into account the aggregation errors. Prior to commencing the task, the subject executed five hits with his right hand on the corresponding sensored hold to synchronize the two systems. Following successful synchronization, the subject performed periodic movements that involved circular motion of the pelvis to evaluate the repeatability of the movement (Figure 5) with hand and feet on the four sensored hold. The Figure 5 depicts the circle task, with the frame sequence extracted from the processed video using MCoM.

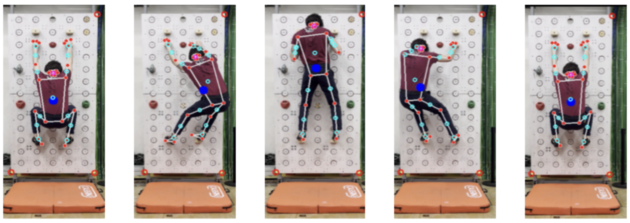


Figure 5: Circle Task.

3. Results and Discussion

3.1. CoM Estimation: MCoM vs VCoM

MCoM was compared against the gold standard VCoM system in estimating the Center of Mass during static and dynamic tasks. Results showed that MCoM provided precise estimates of CoM in orthostatic position without oscillations in both views, but had difficulty tracking oscillations in dynamic tasks from the lateral view. The findings of the study indicate that MCoM can effectively estimate the CoM for tasks where the subject is facing forward. Additionally, the results suggest that caution must be exercised when using MCoM with a side camera. Figure 6 illustrates the y-coordinate of both MCoM and VCoM systems during five squat.

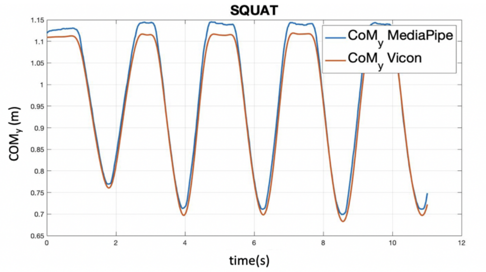


Figure 6: Y-Coordinate Trend During Squat Exercise.

For each task, the Root Mean Square Error (RMSE) was calculated for each trial. Boxplots were then generated to provide a statistical representation of the RMSE population of trials for each task's three coordinates of the Center of Mass. The median and interquartile range (IQR) of the RMSE population for the three coordinates in each of the three tasks are presented in Table 1.

Task	Coordinate	Median(cm)	IQR
Standing	CoM_x	0.5414	0.2935
	CoM_y	1.3318	0.7792
	CoM_z	0.7792	0.7549
Overhead Squat	CoM_x	0.6924	0.2732
	CoM_y	1.5722	0.4696
	CoM_z	4.8719	4.8719
Lateral Squat	CoM_x	1.1567	0.2674
	CoM_y	1.7462	0.5229
	CoM_z	3.2159	0.8078

Table 1: Median and IQR of the RMSE population for each task's three coordinates of the Centre of Mass.

The results show that MCoM is more accurate in the front-view (x and y coordinates) but less accurate in the lateral view (z coordinate), which could be attributed to occlusion caused by the subject's position in the lateral view.

3.2. 3D Centre of Mass in climbing wall acquisition using WCoM

This section compares the low-pass filter and Kalman filter techniques used to estimate the WCoM during climbing wall tests. Figure 7 provides a direct comparison of the 3D trajectory of the task obtained using both techniques. The low-pass filter produces a smoother trajectory, whereas the Kalman filter, despite correcting the z-position estimate, generates a noisier output.

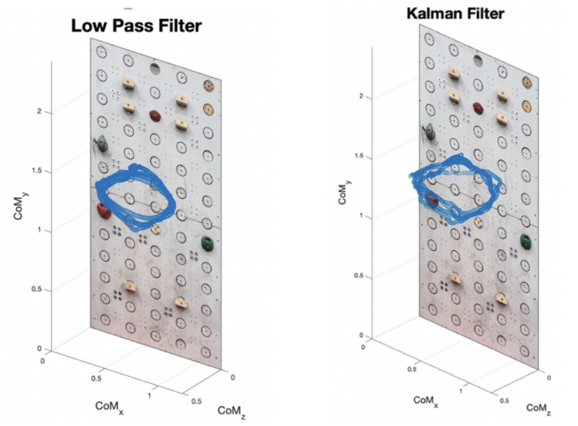


Figure 7: 3D Trajectory of Centre of Mass during circle task.

The Figures 8 and 9 show the comparison of the z coordinate of the WCoM using both the low pass filter and Kalman filter with the benchmark MCoM.

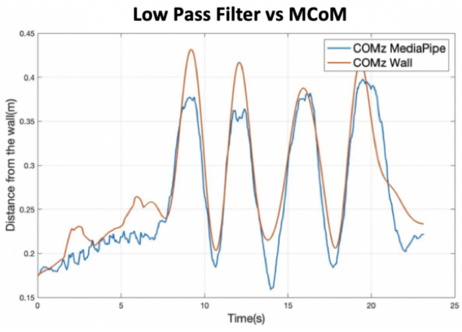


Figure 8: CoM_z using Low pass filter.

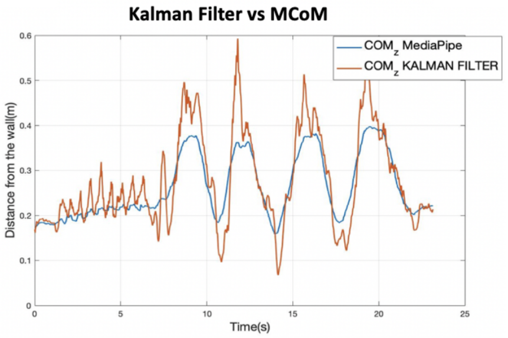


Figure 9: CoM_z using Kalman filter.

Both Figure 9 and Figure 7 illustrate that the use of the Kalman filter produces a less accurate and noisier signal compared to the low-pass filter for estimating the WCoM. As a result, despite being a simpler and computationally less demanding technique, the low-pass filter was chosen as the most effective method due to its smoother and more accurate output.

To evaluate the accuracy of WCoM using the low pass filter, the study developed a method to assess the error of WCoM in comparison to the gold standard VCoM for the z-coordinate. This was achieved using an error aggregation method designed to evaluate the error of WCoM (E_W). This method assumes that the error of WCoM with respect to MCoM (E_{WM}) and the error between MCoM and VCoM (E_M) are normally distributed with a mean equals to zero. Using this assumption, an upper bound of the variance of the error of WCoM (σ_W^2) can be found using the following equation:

$$\sigma_W^2 \leq \sigma_{WM}^2 + \sigma_M^2 + 2 \cdot \sigma_{WM}\sigma_M \tag{3}$$

where σ_{WM}^2 and σ_M^2 are respectively the variance of E_{WM} and E_M and $\sigma_{WM}\sigma_M$ is the product of the two standard deviations of E_{WM} and E_M.

The upper bound defined by Equation 3 was used only to calculate the error of the z-coordinate of WCoM. This is because MCoM is utilized to calculate the x and y coordinates of WCoM, resulting in the same accuracy and variance for E_W and E_M for these two coordinates. The results obtained are presented in Table 2.

Coordinate	σ^2_{WM}	σ^2_W	σ^2_M	$\sigma_W(m)$
Coordinate x	/	2.3×10^{-4}	2.3×10^{-4}	0.0152
Coordinate y	/	3.6×10^{-4}	3.6×10^{-4}	0.0190
Coordinate z	5.6×10^{-4}	7.75×10^{-4}	0.0027	0.0515

Table 2: Variance of the error of WCoM Method.

Table 2 shows that WCoM system provides accurate measurements for x- and y-coordinates of the Center of Mass, with a standard deviation of just a couple of centimeters. However, z-coordinate has a higher standard deviation around 5 cm. While this level of accuracy may be adequate for some applications, it may not be sufficient in the context of climbing, where the position of a climber's center of mass varies significantly and precision is of utmost importance.

4. Conclusion

In recent years, there has been a growing interest in developing minimally invasive technologies that can be used to analyze human motion in real-life contexts outside of the laboratory. This shift is being driven by a desire to reduce the time and resources required for complex machine calibration and to ensure that the movements being analyzed are as realistic as possible without the use of markers that could potentially interfere with the motor gestures being studied. Against this backdrop, this study aimed to develop a fully marker-less method for calculating the Center of Mass of a climber. The method involved integrating information from a sensorized climbing wall, which returned force signals generated by the climber's interaction with the wall, and a camera-based system, which used a neural network to reconstruct the climber's 2D pose from video footage. The ultimate goal of this approach was to generate a 3D reconstruction of the climber's Center of Mass trajectory, which is a critical biomechanical parameter for studying the unique characteristics of the sport of climbing that is still under study. However, the initial attempts to extract the Center of Mass trajectory from the force signals returned by the climbing wall were hampered by significant drift caused by the presence of white noise and quantization in the signal. To overcome these limitations, the study incorporated information from a camera-based system, which was able to accurately reconstruct the climber's pose in 2D. Using a geometric model that factored in the various body masses of the climber, the Center of Mass was then extracted in all three directions using both frontal and lateral views of the subject. The accuracy of this method was validated by comparing it to the gold standard Vicon system, which uses the *Plug-in Gait* protocol to calculate the Center of Mass coordinates in all three directions. The results of this analysis showed that the accuracy of the Center of Mass calculation was higher when using the frontal view as compared to the side view. It was hypothesized that the occlusion caused by the subject in the side view could make it challenging for the neural network to accurately reconstruct the pose. The final step involved integrating the video information with the sensorized wall to generate a 3D reconstruction of the Centre of Mass trajectory. The accuracy of the x and y coordinates was directly comparable to the Vicon system, while the magnitude of the error on the z coordinate was validated using a video camera placed laterally.

Overall, this study represents a significant contribution to the field of biomechanics by providing a more comprehensive and accurate way to measure the Center of Mass trajectory in climbing. The findings highlight the potential of computer vision-based methods and sensor-equipped climbing walls to advance our understanding of the intricate movements and forces involved in this challenging sport. However, further research will be needed to fully explore the limitations and broader applicability of this approach in different contexts and populations.

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