Application of OpenPose deep learning algorithm for gait parameter identification

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EXTENDED ABSTRACT

1 Introduction

The systematic study of human gait dynamics has allowed medical professionals to offer personalized treatment to individuals suffering from varying degrees of gait degeneration. Currently, marker based motion capture is regarded as the gold standard of motion analysis [1][2][3]. Nevertheless, it is a very time consuming and fatiguing process, as a multitude of markers need to be carefully positioned on an individuals body. The use of Inertial Measurement Units (IMUs) has facilitated a faster process of recording limb accelerations and velocities during locomotion, allowing the reconstruction and personalized study of the gait dynamics. However, IMUs cannot be used to reconstruct the limbs' positions, unless the individual's initial body pose is known. Currently, the initial body pose is gained via a motion capturing systems, overturning the time benefit of the IMUs.

In this study we will use the openly available human pose estimation program OpenPose [4][5], to obtain the initial body pose of an individual. We will use the 2D output to measure limb lengths and initial limb angles. Finally, we will evaluate the method's accuracy and efficiency with respect to the established marker-tracking method.

2 Description of OpenPose

OpenPose is a library for real-time multi-person keypoint detection and multi-threading. It represents the first real-time system to jointly detect human body and hand keypoints on single images. In addition, the system's computational performance on body keypoint estimation is invariant to the number of detected people in the image.

OpenPose provides developers with human skeleton data from monocular images using a Convolutional Neural Network (CNN). One can setup OpenPose easily and get position data of body joints on various frameworks of deep learning merely with an ordinary camera. It takes an RGB image as input and produces the 2D locations of anatomical keypoints for each person in the image. The system processes images through a two-branch multi-stage CNN. Each stage in the first branch predicts confidence maps, and each stage in the second branch predicts part affinity fields. First, a feedforward network simultaneously predicts a set of 2D confidence maps of body part locations and a set of 2D vector fields of part affinities, which encode the degree of association between parts. Finally, the confidence maps and the affinity fields are parsed by greedy inference to output the 2D keypoints for all people in the image. [6]

3 Application to Gait Lab test

To test the suitability of the OpenPose library on a gait analysis application, a set of images of a person are used as input, and the their pose is estimated. The program's output includes the identified limb configuration, overlaid on the input image. The identified nodes can be used to calculate each limb's length and orientation on the image plane. The procedure is repeated for front, back and side views. This provides an estimation of the individual's pose, as projected on the respective image planes. The OpenPose output can be observed in Figure 1, where it can be seen that the pose is correctly estimated for the visible limbs, while some inaccuracies occur for the limbs that are mostly out of view.

(a) Front View (b) Right Side View (c) Back View (d) Left Side View

Figure 1: OpenPose output for the tested views

4 Validation with Vicon

The marker based Vicon motion capture system is currently employed in the UDE Gait Lab using a Plug-In-Gait model. From the recorded data, the limb lengths are calculated using the computed joint centers.

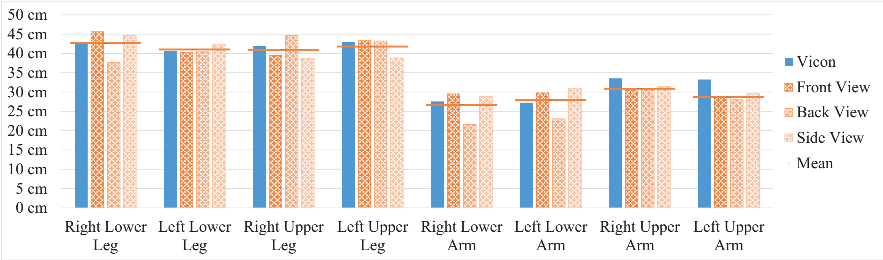

Figure 2: Comparison of limb lengths Vicon vs. OpenPose

To quantify the accuracy of OpenPose, the results obtained by OpenPose are compared with the results obtained from the Vicon system, using the same set of images. Figure 2 shows the comparison of the computed limb lengths from the Vicon system with the ones obtained using OpenPose. Overall, the results are promising, especially looking at the average of images from different sides, given that the OpenPose results are obtained using only a set of four pictures from various angles.

5 Conclusions and future work

As can be seen in Figure 2, the limb length estimations performed by the Vicon system and OpenView are in close agreement for most of the analyzed views. Only the upper arms vary considerably, which could be the result of different definitions in Vicon joint centers and OpenPose nodes. The OpenPose results from analyzing the back view present some estimation errors as well: this kind of errors are due to optical effects such as lens distortion or loss of scale in the mono camera.

A calibrated, multi-view imaging setup is needed to maximize the estimation accuracy. For this reason, a set of cameras will be placed in precise locations and will be calibrated, in order to better account for the effects of varying scale due to lens distortion. These cameras will be used to simultaneously capture different views of the body pose. If the relative placement of different-view image planes is known, it will be possible to obtain accurate estimates of the limbs' 3D position and orientation. It is also necessary to compare the definitions of the Vicon joint centers and OpenPose nodes.

Overall, the pose estimation process is significantly accelerated by using OpenPose instead of the Vicon system, as no preparation is needed for the proposed setup and while the computation time is in the order of seconds. As a next step, multiple body poses will be used to obtain a more accurate estimate of limb lengths in any individual. This information can be used to improve the model and finally obtain a better estimation of the initial body pose. We believe that the advantages of the OpenPose library can significantly improve the efficiency of the IMU initialization procedure, while its drawbacks can be overcome by the use of a more structured imaging environment.

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