Gait analysis using video for disabled people in marginalized communities

Achilles Vairis[1] [0000-0001-6359-799X], Johnathan Boyak[2] [0000-0003-1790-5335], Suzana Brown[2] [0000-0002-2184-1701], Maurice Bess[2] [1111-2222-3333-4444], Kyu Hyun Bae[2] [0000-0002-1925-8816], Markos Petousis[1] [0000-0003-1312-7898]

[1]Hellenic Mediterranean University, Greece
[2]State University of NY Korea., Korea
suzana.brown@sunykorea.ac.kr

Abstract. The goal of this project is to remotely analyze the gait of people walking with crutches. To that objective, the use of video analysis based on the open-source software OpenPose is compared with the data collected from a sensor mounted on a human subject. The results show that the average value of acceleration between the video analysis and the sensor differs by 0.05%. All steps are clearly identified and synchronized. As a consequence, it is possible to validate non-contact acceleration data from video analysis with an inexpensive setup described in this paper. The results show a promise that this non-contact method can be used to assess the gait of disabled people with assistive devices in remote locations.

Keywords: Gait Analysis, Disability, Video analysis, OpenPose

1 Introduction

The current study aims to design better-suited mobility aids for people affected in insecure areas. A particular site for testing a design is a refugee camp in Bangladesh, specifically erected for the Rohingya people immigrating from Myanmar. Approximately 909,000 Rohingya refugees live in 34 highly congested camps. Since the humanitarian crises hit vulnerable groups hardest, such as people with disabilities, the goal was to improve the mobility of people with disabilities in navigating environmental obstacles in these limited-resource settings.

One challenge for this project was during the baseline study to remotely assess issues in the gait of the disabled population in a refugee camp in Bangladesh, so the team investigated the use of video analysis. The video analysis is based on the open-source software, OpenPose, which was developed in 2017 by the Carnegie Mellon University Perceptual Computing Lab. The software is based on Convolutional Neural Networks (CNN), and it can precisely identify 135 joint points on a human body. OpenPose can be used to capture either individual or multiple persons on a single image.

This study presents initial results in the lab while the team was assessing the suitability of the approach. This paper is also evaluating the use of the human computer interface (HCI) approach in low-resource settings, termed HCI4D or HCI for development, and the usefulness of OpenPose for remote gait assessment.

The main contribution of this paper that, to our knowledge, it is the first attempt to use video analyses software such as OpenPose to perform gait assessment.

2 Related work

2.1 HCI4D

HCI4D research has been focused on development, low-resource settings, and/or marginalized groups [1]. In addition, some researchers viewed HCI4D as research defined by the location and certain infrastructural constraints, as well as motivated by regards for social justice [1]. It has been argued that user centered design and evaluation techniques do not easily translate from the Global North to the Global South, therefore they should be adapted to new cultural contexts and settings [2]. In addition, one of the ways to broaden the agenda in HCI is supporting marginalized communities [3]. For example, designing technologies to support low-income rural women in Bangladesh [4], which expands the HCI community's understanding of technology design within deeply patriarchal societies. The current study is aiming to support the marginalized population of disabled users in need of mobility support such as crutches. The intended users are Rohingya refugees but the diagnostic tool is useable for any distance gait evaluation by using a video tool.

2.2 Gait studies

Gait analysis is the evaluation of the manner or style of walking usually done by observing the human as they walk in a straight line. This evaluation is commonly performed in two different ways. The first is by empirical analysis, while the second is based on sophisticated instrumentation measuring body movements, body mechanics and activity of the muscles. Various studies have been carried out using different tools such as force platform, optical markers and 3D-cameras. These motion capture systems are expensive and must be installed in appropriate rooms containing cumbersome expensive equipment and operated by trained personnel [5].

A simple way to analyze the motion is to use accelerometers. In motion analysis, the main interests are activity recognition [6] and the detection of specific gait events (e.g. falls). Most research on fall detection uses linear acceleration and gyroscopes. They typically detect falls by applying thresholds to accelerations, velocities and angles [7]. However, the performance of these systems depend strongly on the position of the sensors (e.g. the wrist, waist, ankle) [7-8].

A popular current research challenge has been on the authentication of users based on gait recognition [9]. The research focused on the identification of a person based on the way that they walk using dynamic time warping [10]. However, during a natural walk, a person could change the way that they walk making it difficult for identification. A study most comparable to the current study uses video for gait analysis by detecting walking behavior based on the motion transfer by the user on the walker [11].

In recent years OpenPose software has been widely used for gait analysis. OpenPose is an open-source software that is a real-time multi-person system designed to detect human body, hand, facial, and foot key points on images. It has been shown that OpenPose algorithm can learn to associate body parts with individuals in the image [12], that is reliable and valid in tracking bilateral squats [13], and an assessment system for a gross motor action recognition of preschool children [14]. To our knowledge no other study used OpenPose to access gait dynamically.

2.3 Theory

The current approach is leveraging an activity theory, a conceptual framework originally developed by Aleksei Leontiev. The essential concept of this theory is human activity, which is considered to be purposeful, mediated, and transformative interaction between human beings and the world. Along with some other frameworks, such as phenomenology and distributed cognition, activity theory established itself as a leading post-cognitivist approach in HCI [15]. HCI researchers use activity theory as a theoretical framework for empirical analysis to formulate specific questions for their studies for technology use in controlled experimental settings. One example closest to the present approach is a study that determines if hand posture can be used to determine the types of interactions in a desk/office environment [16].

3 Methodology and Data

Two iPhone 6s with 8-megapixel cameras were set up on tripods and placed at a distance that allowed for 30 frames per second video capture of several steps when using a swing-through gait[1]. The cameras were arranged to provide a stereoscopic view of the run, with one recording the side view of the walk and the second camera, at 90 degrees to the first camera, recording the subject walking towards the camera. The two cameras were calibrated using a large checkerboard pattern to obtain the stereoscopic transformation matrix, which was used to obtain the 3D position data of an object in the covered area. A healthy male subject used axillary crutches and was instrumented with an accelerometer sensor firmly attached to his walking ankle while the video was recorded. The sensor setup attached to the leg of the subject (see Fig. 1) was the GY-521 module,

[1] The swing-through gait requires the user to place both crutches ahead of themselves and swing both feet past the crutches to the next position. When performing a swing-through gait, the user's full body weight becomes temporarily supported by the crutches.

which includes a gyroscope packaged together with a three-axis accelerometer connected to an Arduino Uno microcontroller together with a micro SD card for data collection. The protocol employed started with an initiation step (foot tap) and return to the initial position to signal the start of data collection. A short pause followed this initial step and steps with crutches were recorded using the stationary cameras.

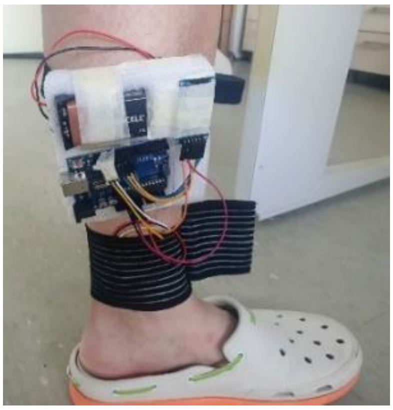

Figure 1 Sensor attached to a leg of the test subject.

The raw velocity data obtained from the sensors mounted on the healthy subject is presented in Figure 2. From the velocities in three global coordinates (X, Y, and Z), we can identify individual steps. For comparison purpose, the horizontal axes in the plots are in time counts measured by the sensor and not in time units such as seconds, while the vertical axes units are in relative units, measured by the sensor. The velocity on the X axis (which is along the direction of movement) shows three steps that are in phase with the three steps shown in the Y axis (which is perpendicular to the floor). This is predictable as the foot moves in those two directions during each step. The same is true for the relative value of velocities between those two axes, as the forward movement of the foot results in the X velocity components being much larger than the ones in the Y direction. The third velocity component in the Z axis (which is along the floor, as the X components, but perpendicular to the other two components) shows depressions matching the steps of the other components, but at a much lower value than the X axis velocity. This results from the fact that the healthy subject’s walk does not include a complex foot movement in space. In contrast, a disabled person may have a complex or even unstable foot movement, in which case there would be a much stronger Z velocity component. All traces in the three directions have practically zero value during the stance stage of the walk.

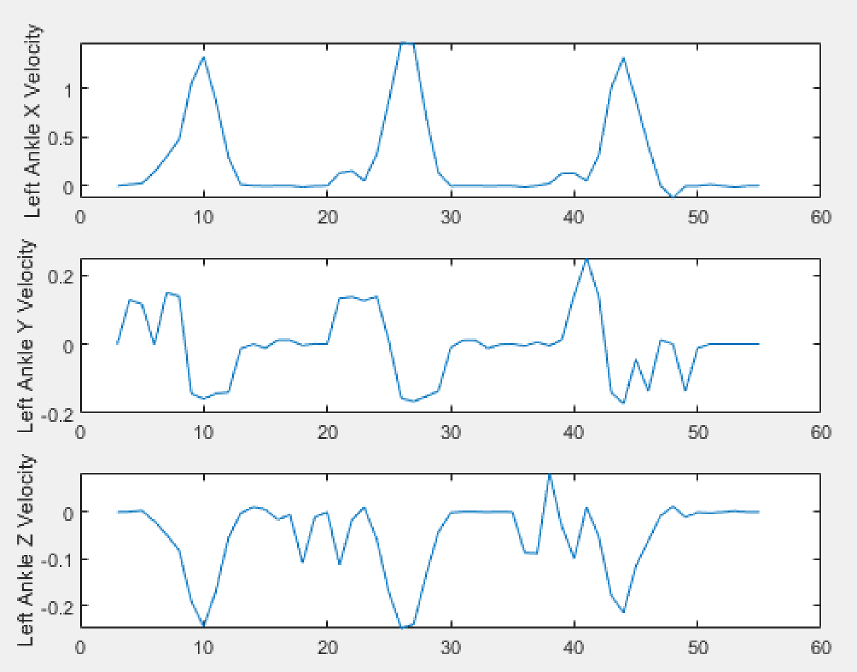

Figure 2 Velocities XYZ

Subsequently, the raw data from the sensors are combined using the square root of the sum of the squares of the accelerations in the primary directions to produce the total acceleration experienced by the left ankle shown in Fig. 3. This equation is

$$Acc_{Total} = \sqrt{Acc_x^2 + Acc_y^2 + Acc_z^2}.$$

In addition, because of the complex movement of the foot in all three axes, the combined signal was further processed using the moving averages which smooths out the calculated acceleration while retaining the key characteristics. After the processing, the individual steps are clearly identifiable while the stance period is stable and close to the acceleration of gravity (g). This operation allows for the qualitative identification of individual steps as it removes the signal fluctuations. One possible source of errors in the acceleration measurements may come from drift [18] in relative movement between the mounted sensor box and the body. However, measurements with the sensors mounted on the subject allow identification of the gait. As a consequence, it is possible to validate non-contact acceleration data from video analysis with this inexpensive setup.

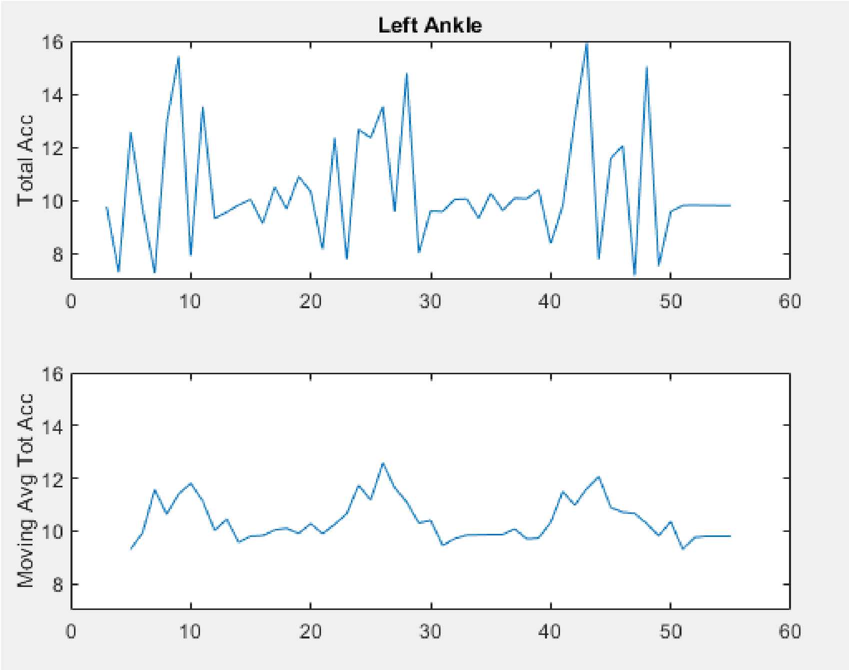

Figure 3 Total acceleration

With that objective, Fig. 4 combines on the same graph the raw data from both the accelerometer and the video analysis. Each step, both the initial and the walking steps, can be identified as a complex waveform. The step waveform for each source, the accelerometer and the video analysis, are different because of the nature and accuracy of the medium.

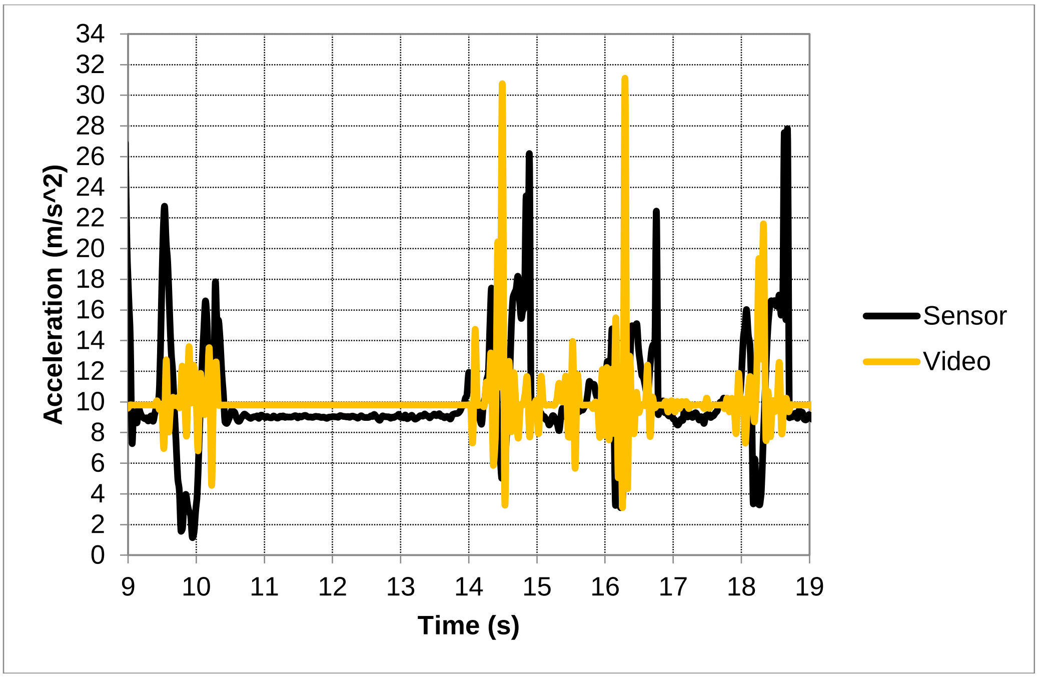

Figure 4 Raw data from video and sensor data

Fig. 5 shows the processed acceleration recorded by the sensor and one calculated based on the video. The acceleration calculated from the video was passed through a low-pass filter with a 6 Hz cut off [17]. The data from the sensors was similarly processed to remove spurious very high acceleration values by cropping excessive values and then calculating the moving average of the signal. The average values of the processed acceleration between the video analysis and the sensor differ by 0.05%.

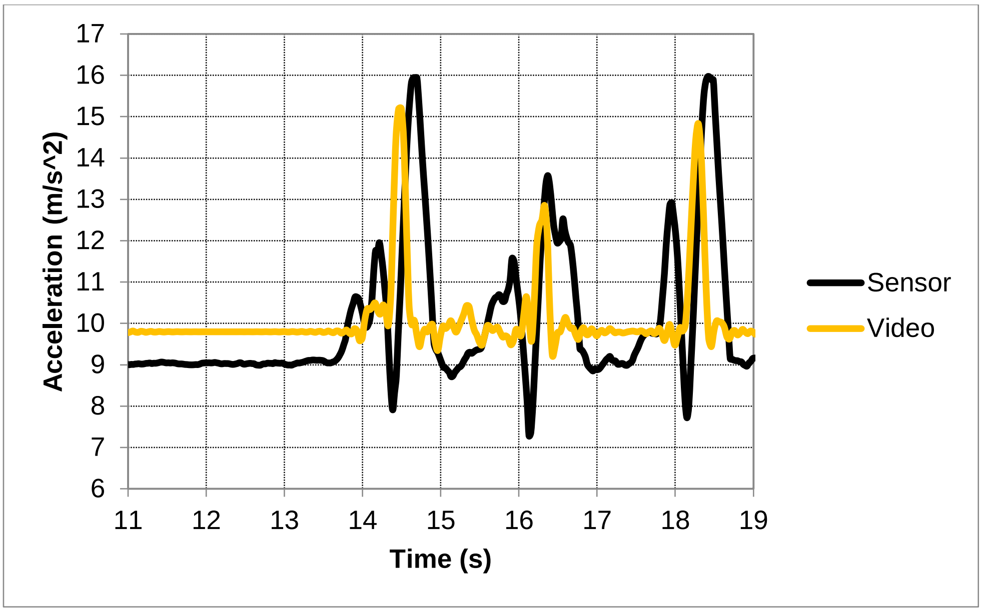

Figure 5 Processed acceleration of video and sensor data

4 Discussion and conclusion

Comparing data from two different methods, video and sensors, it can be seen that all steps are clearly identified and synchronized. The idle stage before walking, at times between 11 and 13.6 sec, and the intermediate stages between steps, for example, between 16.8 and 17.8 secs, can be identified. Distinctive features of the acceleration from the sensor data are observed. Each step of the specific gait is represented by two maxima with a minimum value between them. These features cannot be identified in the video signal because the video is less sensitive to minute and fast changes in the acceleration and it identifies steps with single maxima. These differences between two completely different methods are expected because of their modes of operation. The sensors were strapped to the subject's ankle accurately following the movement but they have a limited relative movement to the actual bone, while the acceleration depends on the orientation of the sensor during walking [7-8].

The acceleration calculated from the video analysis is calculated from the ankle movement using OpenPose. The software interprets each video frame separately identifying the various limbs of the person, and the time sequence of the spatial data allows the calculation of acceleration. As the software works on individual frames, minute differences in the pictures do not affect the identification of limbs but they affect the precise position of an ankle and limit the accuracy of accelerations. After the data was processed, the differences between the signals were minimal but the level of detail that the sensor provided was greater than the video signal. The main advantage of using a non-contact method, such as video analysis, to extract mechanics quantities, is that it is a fast and inexpensive method available in many real-life settings.

The results with OpenPose are promising. However, there are other multi-person pose estimation systems such as Alpha Pose[2], which is capable of following the same person across frames, that could provide more accurate measurements. Future work will consider such alternatives to verify video analysis for gait assessment. The goal of the current study is to contribute to the cost reduction of gait assessment. One benefit will be to reliably evaluate the gait of disabled people in remote locations. Future work is needed to verify that this non-contact method of video analysis can be used to assess the gait of disabled people with assistive devices in remote locations.

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