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Design of an experimental platform for gait analysis with ActiSense and StereoPi

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Abstract: Gait analysis is a systematic study of human movement. Combining wearable foot pressure sensors and machine learning (ML) solutions for a high-fidelity body pose tracking from RGB video frames could reveal more insights into gait abnormalities. However, accurate detection of heel strike (HS) and toe-off (TO) events is crucial to compute interpretable gait parameters. In this work, we present an experimental platform to study the timing of gait events using a new wearable foot pressure sensor (ActiSense System, IEE S.A., Luxembourg), and Google's open-source ML solution MediaPipe Pose. For this purpose, two StereoPi systems were built to capture stereoscopic videos and images in real time. As a proof of concept, MediaPipe Pose was applied to one of the synchronised StereoPi cameras, and two algorithms (ALs) were developed to detect HS and TO events for gait analysis. Preliminary results from a healthy subject walking on a treadmill show a mean relative deviation across all time spans of less than 4 % for the ActiSense device and less than 16 % for AL2 (33% for AL1) employing MediaPipe Pose on StereoPi videos. Finally, this work offers a platform for the development of sensor- and video-based ALs to automatically identify the timing of gait events in healthy individuals and those with gait disorders.

Keywords: Human gait, Risk of falls, Computer vision, Pose estimation, Stereoscopic cameras, Foot pressure sensors.

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1 Introduction

Walking is crucial for independent mobility, activities of daily living, and quality of life [1]. Physical and mental impairments often cause measurable differences in a person's gait pattern, such as a decrease in velocity, shorter step, and stride length, as well as changes in step width [2]. These differences could affect dynamic margins of stability, especially in the elderly, and increase the risk of falls [2]. The analysis of human gait has applications in sports, physical rehabilitation, clinical assessment, and many other fields [3]. Gait patterns are mainly characterised by differences in limb movements, a person’s velocity, ground reaction forces, and changes in ground contact [3]. Several platforms are available on the market to identify gait patterns and validate the accuracy of estimated gait events including video images, force plate measurements and pressure sensing platforms [3]. However, most techniques are limited to expensive gait analysis laboratories such as instrumented walkway and do not necessarily reflect the dynamics of gait while walking in non-laboratory environments [2].

Body-worn sensors such as accelerometers are most commonly used for gait measurements outside the laboratory [3]. Here, force sensitive resistors or foot switches have the potential to evaluate the accuracy of an accelerometer-based gait analysis system [1], [3]. Recent developments combine insole-based force sensing resistors with accelerometers such as the ActiSense System (IEE S.A., Luxembourg [4]) to support diabetic patients in monitoring their health status [5]. Such a system could be used without additional equipment, cost, or inconvenience to examiners or patients.

In addition, recent studies show advances in 2D video-based pose estimation for automated movement analysis [6]. The learning algorithms (ALs) at the core of human pose estimation solutions use networks that are generally trained on large datasets containing images of different individuals [6]. This often results in robust networks that are capable of detecting body landmarks in new images beyond the training dataset. However, there remains a critical need to evaluate those video-based approaches [1].

In this work, an experimental platform for the analysis of gait events is presented, which provides comprehensive access to hardware and software components by combining a smart insole-based foot pressure sensing device (ActiSense System) with stereoscopic cameras (StereoPi) for a 2D video-based pose estimation (Google’s MediaPipe Pose). StereoPi is an open-source stereoscopic camera based on Raspberry Pi [7]. The low-cost system can capture and process real-time stereoscopic video and images. It opens up countless possibilities in robotics, virtual reality, computer vision and many other fields [7]. MediaPipe Pose is a machine learning (ML) solution for body pose tracking, interfering 33 landmarks and a background segmentation mask on the whole body from RGB video frames utilizing Google’s BlazePose research [8].

2 Methods

This work describes the design of an experimental platform for gait event analysis which combines the ActiSense System and a custom-built StereoPi system. ALs were developed for gait event detection using Google's MediaPipe Pose ML solution. Both systems are used to detect and compare critical gait events. To estimate gait parameters of each gait cycle associated with the stance and swing phase, the detection of heel strike (HS) and toe-off (TO) events are crucial [3]. Both events were detected by the ActiSense foot pressure signals and estimated locations of the pose landmarks (left/right ankle, heel, and foot index) using the MediaPipe Pose ML model employed on the synchronised StereoPi system. Additionally, the foot pressure sensor measures the ground contact force (appears in stance phase) which has a significant impact on the walking stride of a person. As a proof of concept, a healthy subject (female, 23 years old) walked on a non-instrumented treadmill to generate gait data. The data set comprises 4 data sequences from the synchronised StereoPi system and ActiSense foot pressure signals.

2.1 ActiSense System

The ActiSense system (IEE S.A., Luxembourg) was used to measure human gait. Figure 1 shows IEE's sensor prototype, which measures foot pressure in real time, ranging from 250 mbar to 7 bar [4]. The electronics unit has an integrated accelerometer and gyroscope. Foot pressure, acceleration, and angular velocity signals are internally synchronised and were recorded at a frequency of 200 Hz. The time series data were analysed offline with custom-written software in MATLAB™ (R2020a, MathWorks Inc., USA). For this purpose, a Gaussian filter (δ is 5, the number of coefficients is 7) was applied to smooth the pressure signals. To detect the gait events of HS and TO, a simple threshold detection method was employed on the foot pressure signals. A set of fixed, observable thresholds was defined for each recorded data sequence.

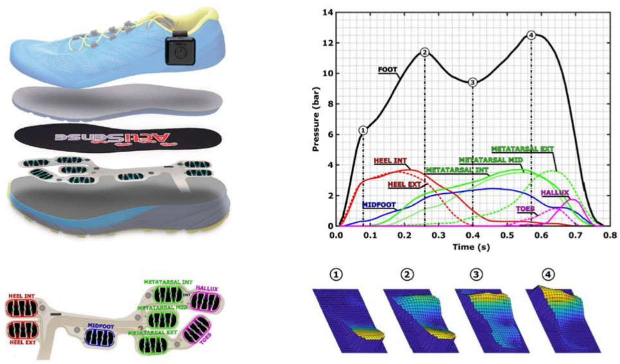

Figure 1: IEE’s ActiSense system, consisting of an electronic control unit (black enclosure, top left) and an insole comprising 8-high-dynamic pressure cells (bottom left). Illustration of a typical walking pressure profile (top right), including a 3D foot plantar load distribution reconstruction (bottom right). [4]

2.2 StereoPi cameras

The StereoPi system built for this work, consists of two StereoPi boards V1 and two Raspberry Pi Compute Modules 3 Lite. Figure 2 shows the system which operates two pairs of Raspberry Pi cameras V1 simultaneously and is designed to record stereoscopic images and videos.

Figure 2: StereoPi system with Open CV image, build from two StereoPi boards, two Raspberry Pi Compute modules and four Raspberry Pi Cameras.

The camera modules are built on OmniVision’s 1.4-micron OmniBSITM pixel architecture. The OV5647 offers high performance 5-megapixel photography with a maximum image transfer rate of 15 frames per second (fps) (2592 x 1944 pixels) [7]. For the detection of HS and TO events, we used 30 fps with an active array size of 640 x 480. For data acquisition, each of the four cameras were integrated in angle-adjustable housings and mounted on adjustable tripods (Figure 2). The StereoPi cameras were positioned on the side of the treadmill to capture the entire body of the healthy test subjects.

The StereoPi boards were synchronised by wiring their peripheral general-purpose inputs/outputs (GPIOs). Voltage changes on the GPIOs in combination with software interrupts are used to trigger the videos synchronously. Once a video recording is triggered via a command in the terminal, the software part communicates with the GPIO driver. A Python script sets the GPIOs and synchronises the Raspberry Pis' [7]. However, to control the timing of the trigger pulse, a new script was written in C++. Test recordings showed a delay ranging from 10 ms to 70 ms caused by the synchronisation via the GPIOs. The cameras were calibrated using the calibration script in StereoPi OpenCV library to computes the focal length, centring of the sensor on the optical axis, and the lens distortion.

2.3 Development of algorithms for gait event detection

Two ALs were developed in Python to detect the gait events HS and TO, based on the estimated MediaPipe Pose landmarks imprinted in each video frame. As a proof of concept, we tested the ALs with a single StereoPi camera placed on the right side of the treadmill. To detect both gait events in pre-recorded videos automatically, the angles between the estimated pose landmarks (x and y coordinates) on each foot with respect to the hip were calculated with AL1 (four angles). Since the calculation of two angles for both legs could be sufficient, AL2 was introduced for comparison. Figure 3 illustrates both ALs.

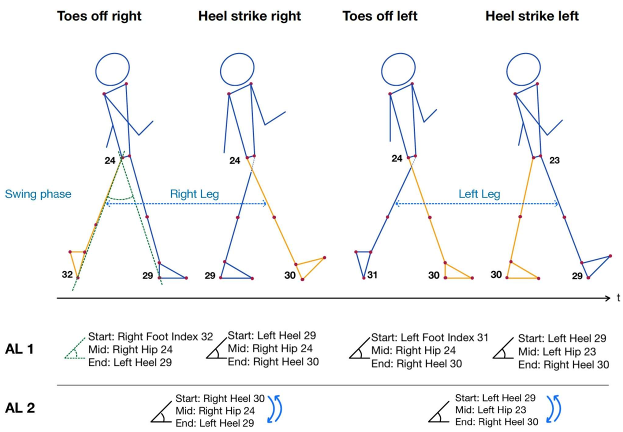

Figure 3: Schematic sketch of the angle calculations for both ALs based on MediaPipe's landmarks. AL2 applies in both directions.

In order to calculate the angles, we consider the lower extremities as a pendulum; when an event occurs, the corresponding angle is maximum. For this purpose, the actual value of an angle is compared with the previous and penultimate value. To trigger an event, the previous angle has to be larger than the actual and penultimate angle. Subsequently, the time difference between the triggered events is used for analysis and displayed in a status box in the processed videos.

If at least two consecutive gait events are detected by one of the ALs, the two corresponding time stamps are used to calculate the time difference between both gait events. Subsequently, the ALs splits the videos into single frames and each frame is analysed individually by MediaPipe Pose. In the next step, the ALs calculates the angles based on the extracted landmarks as illustrated for AL1 in Figure 3. Both ALs were compared to the video. The gait events were manually labelled by visual inspection of the video frames and served as video reference labels (VRLs).

3 Results

The healthy subject walked on a non-instrumented treadmill for 60 s with an adjusted speed of 4 km/h. Table 1 shows the results of the gait event analysis and Table 2 some details. A total of 84 HS and 83 TO events were counted, resulting in 41 gait cycles for each leg side. Consequently, we labelled 167 gait events in the recorded video (one TO right event excluded). The mean relative deviation in Table 1 is defined as the average of all time spans between two consecutive events detected by the ALs with respect to the VRLs. Table 1 shows a mean relative deviation of less than 33 % for AL1 and 16 % for AL2 using MediaPipe's landmarks. Both ALs detected all TO events.

Table 1: Comparison of the two ALs with the VRLs captured from the StereoPi video.

Gait event *	Video	Algorithm 1				Algorithm 2			
	Number of events	Detected events		Mean absolute deviation (s)	Mean relative deviation	Detected events		Mean absolute deviation (s)	Mean relative deviation
HSL	42	13	31 %	0.148	30 %	5	12 %	0.129	26 %
TOL	42	42	100 %	0.100	40 %	42	100 %	0.087	15 %
HSR	42	24	57 %	0.147	31 %	2	5 %	0.054	11 %
TOR	41	41	100 %	0.073	26 %	41	100 %	0.062	15 %
	167	120			**32%**	90			**15%**

* Heel strike left, HSL; Toe-off left, TOL; Heel strike right, HSR; Toe-off right, TOR.

AL1 detected a higher number of HS events compared to AL2 (Table 1). In contrast, the deviations of the determined time spans to the VRLs by AL2 are smaller than the deviations by AL1. However, a considerable number of HS events on both feet were overwritten by TO events within a frame. These pose estimation errors were caused by time delays in the detection of HS events when the succeeding TO event had already occurred. In addition, the ActiSense System was compared with the VRLs. We have added the results of the two ALs (separated into left and right foot) for completeness. The results of the gait event analysis are shown in Table 3. The ActiSense system detected all gait events when applying the threshold method to the foot pressure signals. Table 3 shows a mean relative deviation on both feet of less than 4 % for ActiSense in relation to the VRLs. In contrast, the mean relative deviation over all time spans, with respect to the VRLs, is significantly higher for both ALs using MediaPipe's landmarks.

Table 2: Examples of gait cycles. Corresponding time spans and deviations of the ALs in relation to the VRLs.

Gaitcycle	Gait event *	Video	AL1	Algorithm 1 to Video		AL2	Algorithm 2 to Video	
		Time span (s)	Time span (s)	Mean absolute deviaton (s)	Mean relative deviation	Time span (s)	Mean absolute deviaton (s)	Mean relative deviation
16 LEFT	HSL	0.500	0.636	0.136	27 %			
	TOR	0.167	0.031	0.136	81 %	0.599	0.068	10 %
16 RIGHT	HSR	0.467						
	TOL	0.200	0.625	0.042	6 %	0.653	0.014	2 %
17 LEFT	HSL*	0.500	0.658	0.158	32 %	0.667	0.167	33 %
	TOR	0.167	0.045	0.122	73 %	0.036	0.131	78 %
17 RIGHT	HSR	0.467	0.588	0.121	26 %			
	TOL	0.200	0.070	0.130	65 %	0.557	0.110	16 %
18 LEFT	HSL	0.500	0.619	0.119	24 %			
	TOR	0.134	0.032	0.102	76 %	0.643	0.009	1 %
18 RIGHT	HSR	0.500						
	TOL	0.167	0.644	0.023	3 %	0.684	0.017	3 %
19 LEFT	HSL	0.500	0.611	0.111	22 %	0.593	0.093	19 %
Detection error over 82 Gait cycles					**32 %**			**15 %**

* The value represents the time span between the previous event (HSL) and the actual event (TOR).

Table 3: Comparison of the ActiSense System with the VRLs recorded from the StereoPi video.

		Left foot	Right foot
Video	Number of Gait events	84	83
ActiSense *	Mean absolute deviation (s)	0.017	0.023
	Mean relative deviation	2.54 %	3.52 %
Algorithm 1	Detected events	55 (67 %)	65 (78 %)
	Mean absolute deviation (s)	0.112	0.100
	Mean relative deviation	28 %	38 %
Algorithm 2	Detected events	47 (57 %)	43 (51 %)
	Mean absolute deviation (s)	0.091	0.061
	Mean relative deviation	16 %	15 %

* The left and right foot pressure insoles detected all gait events.

4 Discussion

The presented setup offers comprehensive access to hardware and software components to study the timing of gait events. This is particularly important for the computation and assessment of spatio-temporal gait parameters. However, a significant number of HS events could not be detected. To solve this occlusion problem as reported in the literature [6], we will analyse the performance of the ALs using video recordings from different perspectives and with different frame rates. The ALs will be applied to all StereoPi cameras for gait event detection from multiple viewpoints. The data could be correlated to improve the detection of HS events. In addition, we will implement methods found in the literature to detect gait events using the acceleration and angular velocity signals of the ActiSense System [3].

Moreover, digital image correlation techniques could be applied on a circular setup with multiple synchronised StereoPi cameras to measure the 3D shape and 3D deformation of the imaged foot. In recent studies, this technique has been used for lower limb imaging to automatically design prostheses [9].

Future work will focus on improving the methods, a systematic gait analysis with the four StereoPi cameras, and the development of ALs for automatic detection of gait events. Hence, will collect gait data from several healthy elderly subjects. The experimental setup presented in this work will be integrated into the MoveSenseAI project in the future to study gait patterns in patients with gait disorders.

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