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Camera-Based Human Gait Speed Monitoring and Tracking for Performance Assessment of Elderly Patients with Cancer

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Abstract—**This paper presents a camera-based device for monitoring walking gait speed. The walking gait speed data will be used for performance assessment of elderly patients with cancer and calibrating wearable walking gait speed monitoring devices. This standalone device has a Raspberry Pi computer, three cameras (two cameras for finding the trajectory and gait speed of the subject and one camera for tracking the subject), and two stepper motors. The stepper motors turn the camera platform left and right and tilt it up and down by using video footage from the center camera. The left and right cameras are used to record videos of the person walking. The algorithm for operating the proposed system is developed in Python. The measured data and calculated outputs of the system consist of times for frames, distances from the center camera, horizontal angles, distances moved, instantaneous gait speed (frame-by-frame), total distance walked, and average speed. This system covers a large Lab area of 134.3 m^2 and has achieved errors of less than 5% for gait speed calculation.**

Clinical Relevance— **This project will help specialists to adjust the chemo dosage for elderly patients with cancer. The results will be used to analyze the human walking movements for estimating frailty and rehabilitation applications, too.**

I. Introduction

Advancing age is a high-risk factor for cancer; up to 60% of all new cancer diagnoses and 70% of all cancer-related deaths happen to adults aged 65 or over [1]. There is a need to personalize cancer treatment among older adults based on their frailty and anticipated tolerance of treatment. The assessments that would be helpful are the measurement of step count, gait speed, and total daily activity level. The time and resources required to perform these assessments greatly limit their implementation. In a recent study of hematologic malignancies conducted with 448 older adults, a 0.1 m/s decrease in gait speed was associated with a 20% increased risk of mortality. It was also associated with 33% higher odds of unplanned hospitalizations and emergency department visits within 6 months [2]. Recent guidelines by the American Society of Clinical Oncology recommend gait speed as a practical assessment of function and physical performance in older adults with cancer [3]. Geriatric Assessment (GA) that includes physical status (PS) is used to estimate risk for chemotherapy toxicity for patients aged ≥ 65 [3].

Currently, oncologists do not have a suitable way to collect comprehensive data on the physical activity or frailty of older adults with cancer. Time and space limitations often preclude the routine adoption of gait speed measurement in the oncology clinic. Present methods generally rely on a one-time cross-sectional measurement in the clinic, which may be prone to measurement error and do not reflect typical day-to-day activities of patients during a day or a week [4].

The present methods for collecting data include camera systems ranging from regular cameras [5]-[8] to infrared cameras [9] for tracking body movements. Camera-based gait speed detection approaches mainly use fixed setups of multiple cameras and a synchronization/processing station, limiting their accessibility to only specific areas. It is also very time-consuming and expensive to manually extract multiple parameters of activities from the videos [10]. The infrared cameras are used to avoid problems caused by lighting variations, shadows, and objects having similar coloration to the background [11]. Infrared in the Kinect system can suffer interference from sunlight, lose precision with increased distance, and sometimes not distinguish between individuals in multi-resident homes [9].

There are a few approaches that do not involve the usage of cameras for human body tracking and gait speed estimation, such as measuring foot pressure and using accelerometers. The foot pressure systems are incapable of estimating the distance moved. The distance moved is a significant parameter for measuring the gait phases [12]. On the other hand, the accelerometer-based designs have the problem of error accumulation and cannot determine displacement accurately due to their integration drift, in addition to being highly dependent on the performance and location of the sensor. In one recent study, there was about 7% error on the average speed [13]. These devices collect data on the steps taken, which is inaccurate for calculating the walking gait speed.

A lab or a room is an ideal environment to monitor the gait speed and trajectory of the human subject. In this paper, we propose a camera-based system that collects tracking data and gait speed information of a walking person. The setup consists of a Raspberry Pi computer, visible-light cameras, and a mechanism to rotate the platform toward the subject. The proposed system is operated by a two-stage procedure: 1) tracking the subject and 2) calculating their gait speed and trajectory. The design overview and operation mechanism of

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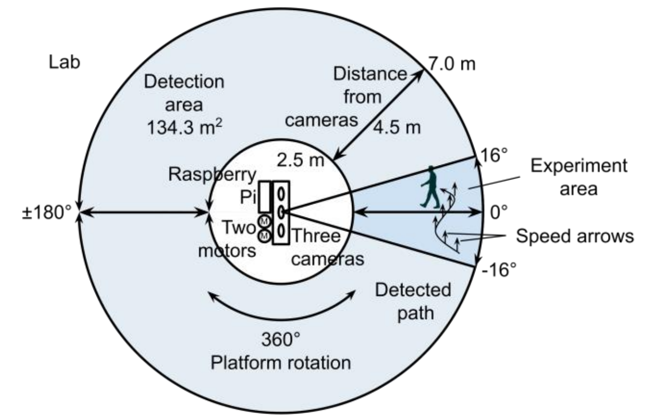


Fig. 1. The proposed solution for subject tracking and gait speed monitoring.

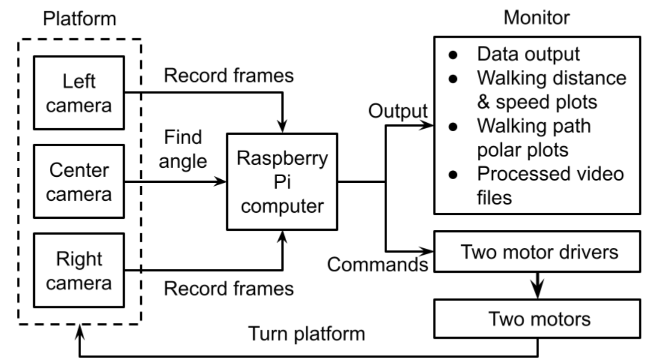


Fig. 2. Hardware block diagram of the proposed camera tracking system.

the proposed system are presented in Section II. Section III includes the experimental results, followed by conclusions in Section IV.

II. Hardware and Software Design Overview

A. Hardware Design

The hardware of the proposed design consists of 1) one RPi 3B+ computer with 1 GB of RAM (a small computer that does not include peripherals such as a monitor, keyboard, mouse, or cameras), 2) two 28BYJ-48 - 5V stepper motors, 3) two ULN2003 driver boards for the stepper motors, 4) gear ratio converter mechanism that gears down at a ratio of 18:1, 5) two cameras (Megapixel 10x digital zoom f=3.85mm USB webcams), 6) one Raspberry Pi V2.1 camera module, and 7) a platform. Fig. 1 shows the coverage area, the setup rotation angles, and the front view of the setup. The hardware block diagram of the proposed system is shown in Fig. 2. This hardware provides all necessary functionalities (with the processor, cameras, and mechanical rotation mechanism) to record multiple videos for tracking and required image processing for gait speed calculation. The distance between the left and right cameras is 249 mm. The range of the rotation angle, left and right, is 360° or ±180°.

B. Software Design

To develop robust software for the proposed design, we have used 1) Python3 programming language (version 3.7.3), 2) OpenCV (cv2) library of programming functions primarily for computer vision (version 3.4.6), 3) Imutils image processing functions (version 0.5.3), and 4) RPi.GPIO library for General Purpose Input-Output through the pins on the Raspberry Pi. The software flowchart of the proposed system is described in Fig. 3. The control mechanism has two main stages, 1) recording and tracking the subject (Fig. 3a), and 2) calculating the gait speed and trajectory (Fig. 3b). The details of these two stages are presented in the following subsections.

C. Subject Tracking Mechanism

There are three cameras in a row on the platform shown in Fig. 1. The center camera is used to find the pixel position of the moving subject to turn the camera platform (camera view) to the center of the moving subject via two stepper motors and a gear mechanism. The process works by assigning the first frame and comparing it with the frames that follow. Differences between the two frames indicate the subject moving. For tracking the subject, a rectangle is placed around the body, and the center of the rectangle is considered the central pixel position of the subject (see Fig. 6a). The image processing includes frame difference, thresholding, dilation, and contouring.

The horizontal field of view of the center camera equals 62.2°. For ease of processing, images are resized to 500 pixels wide and 375 pixels high. The horizontal stepper motor takes 512 steps to turn 360°. The number of motor steps per pixel is (steps/degree)×(degrees/pixel). The number of pixels between the moving object pixel position and the center of the frame is used as a pixel difference. The required number of motor steps is calculated as (motor steps per pixel) × (pixel difference). Before the motors are allowed to move, the cameras record a minimum set number of frames. This is to minimize frequency of camera movement to improve the video capture. After recording, with a moving subject being located, the motors are

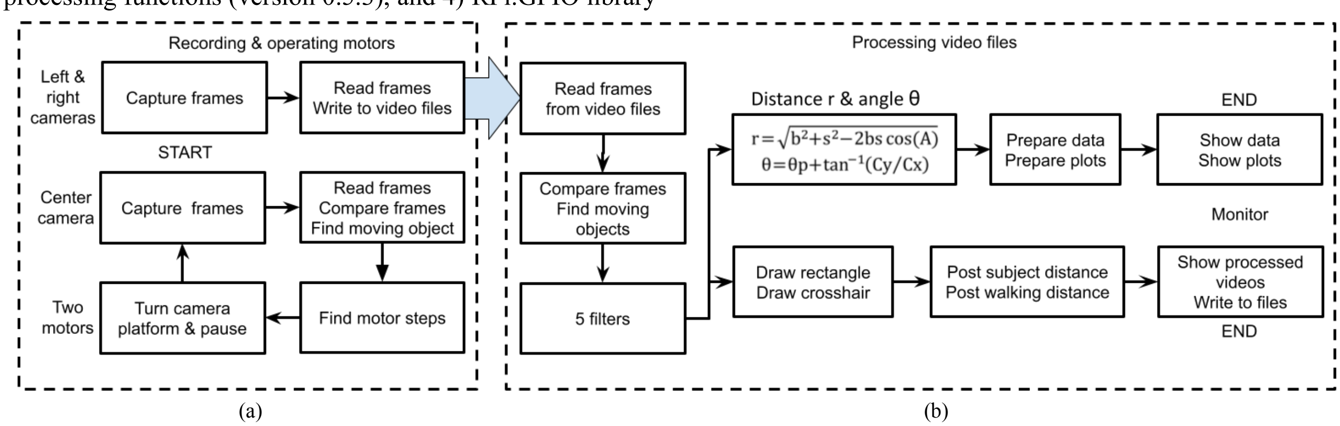
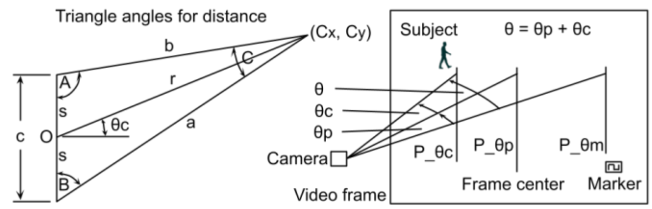


Fig. 3. Software flowchart of the proposed camera-based subject tracking and gait speed-monitoring system; (a) recording and tracking, and (b) processing the video files.



(a) (b)

Fig. 4. (a) Two-camera-based object location finding mechanism, the object distance r and angle θ_C by triangulation, and (b) the mechanism of adding platform angle θp to camera angle θc to get overall subject angle θ.

allowed to turn. There is a pause afterward to allow any shaking to fade. On the next loop, a new frame is taken, and the process repeats.

D. Gait Speed and Trajectory Monitoring Mechanism

The left and right cameras of the platform are used to record video footage from two different angles for calculating the trajectory and gait speed of the subject. The timestamps and platform angle for recording each pair of frames are saved in two lists. The horizontal field of view for the left and right cameras is 21.51°. The frames from those cameras are resized to a width of 500 pixels. The recorded video files from the left and right cameras are processed frame by frame for locating the moving subject. Pixel positions are translated into camera angles to calculate the gait speed and trajectory, in which the distance r is obtained from the top triangle OAC, shown in Fig. 4a, by using sides b and s, and angle A [14], [15].

$$r = \sqrt{b^2 + s^2 - 2bs\cos(A)} \tag{1}$$

The Cartesian coordinates, (Cx, Cy) for point C, are calculated and used to get the camera angle θc.

$$\theta c = \tan^{-1}(\mathrm{Cy}/\mathrm{Cx}) \tag{2}$$

The overall angle θ is obtained by adding the platform angle θp to the camera angle θc.

$$\theta = \theta p + \theta c \tag{3}$$

To find the platform angle θp, a marker is fixed in front of the cameras (in the lower part of the camera view). As shown in Fig. 4b, the angle θ is found by 1) subtracting the center pixel position, $P\_\theta p$, from marker pixel position $P\_\theta m$, (using the center camera) and calculating the platform angle θp,

$$\theta p = (P\_\theta m - P\_\theta p) \cdot R \tag{4}$$

where R = (horizontal field of view/frame width) = degrees/pixel of the camera, 2) subtracting the subject pixel position $P\_\theta c$ from the center pixel position $P\_\theta p$ (using left and right cameras) and calculating the camera angle θc, (2) and 3) using (3) to calculate the overall angle θ of the subject relative to the marker.

III. Experimental Results

The platform with Raspberry Pi, cameras, and motors is shown in Fig. 5. The gap between the left and right cameras equals 249 mm. A fixed marker is used as a reference for getting the platform angle, which is needed to find the subject position (Fig. 5 inset). This marker is located underneath the moving part of the platform and appears in the lower side of

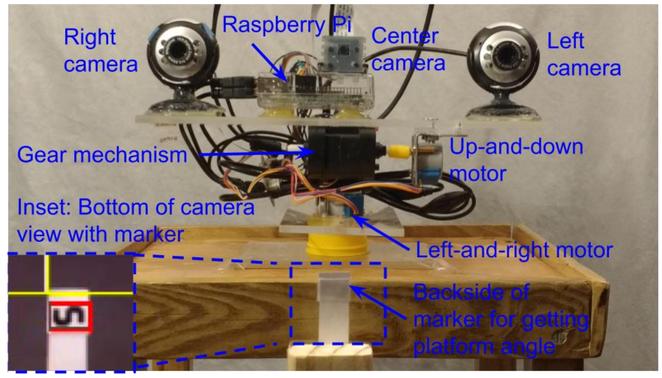
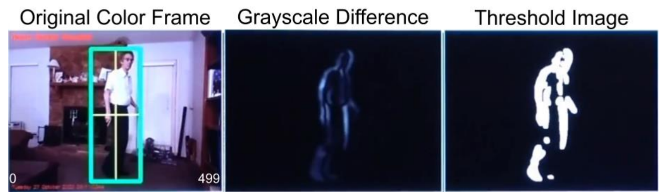


Fig. 5. Implemented platform with Raspberry Pi 3B+, 3 cameras, and 2 stepper motors. Inset: the marker for platform angle detection mechanism.



(a) (b) (c)

Fig. 6. (a) Color, (b) grayscale difference, and (c) threshold images during tracking operation.

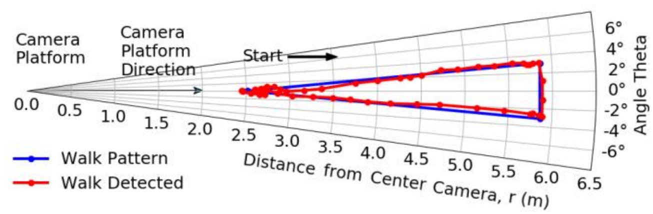
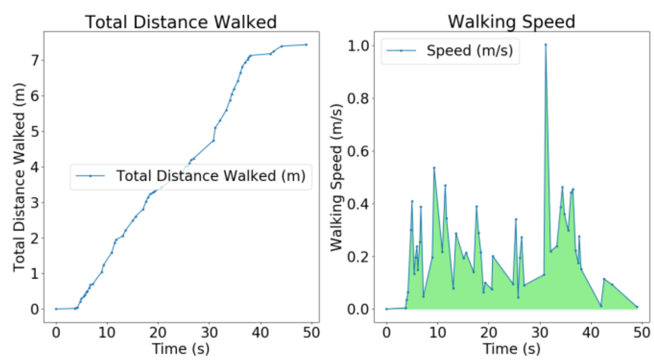


Fig. 7. Triangle walking pattern and detected walking pattern.



(a) (b)

Fig. 8. Measured (a) total distances walked, and (b) instantaneous walking speeds (versus time).

the image (not blocking the subject). Multiple markers can be used if the experiment area needs 360° rotation of the platform.

The developed algorithm averages data values to remove some of the noise or jitter in the data. In the first experiment, the subject (Fig. 6a) walks in three straight lines over a triangular pattern (Fig. 7), in which two lines are almost parallel to the direction of the cameras. Figs. 6b and 6c show the filtering process to detect the subject and find the central pixel position of the subject in the frame. The triangle path pattern (blue) and corresponding detected path (red) are shown in Fig. 7. The detected distances walked and instantaneous gait speeds are shown in Figs. 8a and 8b, respectively. The detected total distance walked is calculated from distances moved between all pairs of consecutive frames (Fig. 8a). The detected

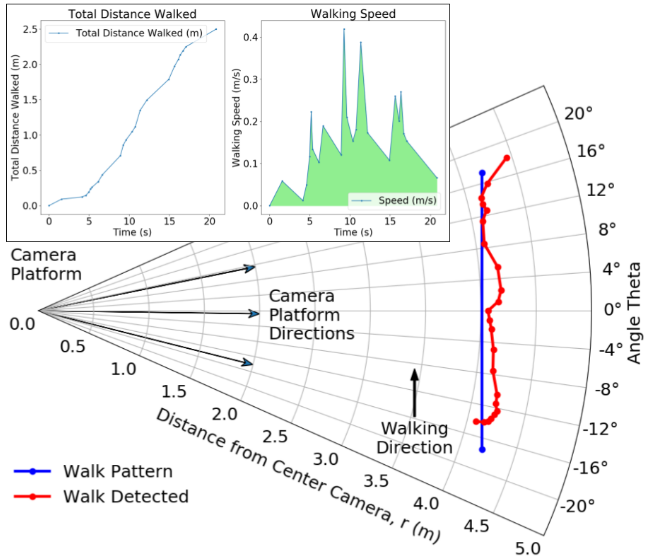


Fig. 9. Plots of straight-line walking pattern and detected walking while the platform is rotated automatically. Inset: Distance walked and detected gait speed.

instantaneous gait speeds are calculated from distances moved and time intervals between consecutive frames, and the results are shown in Fig. 8b.

Fig. 9 shows the experimental results while the camera setup is rotated in various numbers of degrees each time automatically. The resulting camera platform directions are shown by arrows coming from the camera platform at the polar origin. The path detected is compared to a correct path and is shown on a 2D polar plot. The measured results of three different trials are listed in Table 1. The average speed is calculated with two different approaches. Approach 1 is to add all the distances moved and divide by the total time, and approach 2 (only approximate) is to use the calculated speeds for each time interval according to the formula on the last row of TABLE 1. The results were 0.152 m/s and 0.174 m/s in Trial 1 for approaches 1 and 2, respectively.

The challenges of software algorithms being sensitive to lighting variations, shadows, and backgrounds with similar coloring were addressed with various tactics. The subject wore dark or light clothing to contrast with backgrounds of opposite brightness or darkness. The room was illuminated with indirect light to provide bright diffuse lighting that would not cast shadows since a moving shadow could be recognized as part of the moving subject.

IV. Conclusions

This paper has presented our recent progress in developing a camera system to track human subjects by their motion and gather data useful to health assessment, including the trajectory and gait speed. The data from the proposed platform will be used to develop machine-learning algorithms for gait speed recognition to calibrate wearable gait speed monitoring devices. The proposed standalone design has one camera for tracking the subject, two cameras for detecting the trajectory and walking gait speed, a processor, and mechanical equipment for rotating the setup. The implemented camera-based gait speed recognition hardware and software have achieved errors of less than 5% in calculating the distance walked. The device has the capability of working on low average walking speeds of less than 0.3 m/s with a resolution of less than 0.05 m/s. The author plans to improve the system to be more robust in a real world scenario.

TABLE 1. Results from Camera System

Category	Trial 1	Trial 2	Trial 3
Walking pattern	triangle	line	line
Correct walking distance(m)	7.341	2.500	2.500
Detected walking distance (m)	7.426	2.497	2.419
Walking distance error (%)	1.2	-0.1	-3.3
Elapsed time (s)	49.0	20.8	16.05
Average speed =Total distance travelled/Total time taken (m/s)	0.152	0.120	0.151
With n data points, Average velocity = $\{\sum_{i=1}^{n-1}[(\mathrm{time}_{i+1} - \mathrm{time}_i)(\mathrm{speed}_i + \mathrm{speed}_{i+1})/2]\}$/total time (m/s)	0.174	0.135	0.161

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