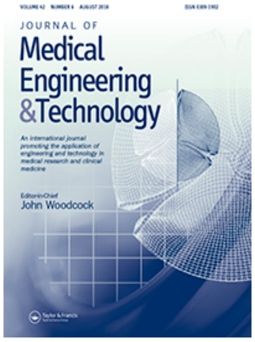

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RESEARCH ARTICLE

Design and validation of a simple automated optical step counting method for treadmill walking

Joseph M. Mahoney[a], Zackery E. Scalyer[b] and Matthew B. Rhudy[a]

[a]Department of Mechanical Engineering, The Pennsylvania State University, Reading, PA, USA; [b]Department of Kinesiology, The Pennsylvania State University, Reading, PA, USA

ABSTRACT

Background: Reliable step counting is a critical part of locomotion research. Current counting methods can be inaccurate, time consuming, expensive or encumbering to the subject. Here, we present a camera-based optical method for automatically counting steps.
Methods: Fifteen healthy adults walked, jogged and ran on a treadmill at three different constant speeds (1.21, 2.01, 2.68 m/s) and once at varying speed (1.21–2.68 m/s) for 90 s. Subjects had visual marker affixed to their left foot while walking. Video was recorded synchronously at low- and high-resolution during trials. The step count found manually from the video was compared to an automated video analysis system using the two configurations of the optical system.
Results: Bland–Altman plots, Intra-class correlation coefficients (ICC) and relative error comparison were used for quantitative assessment of device reliability. Reliability of optical method was high (ICC $\geq$0.98).
Conclusions: The method produces accurate step count results for the range of speeds tested. They use customisable open-source software and off-the-shelf hardware. The method has a low cost of implementation compared to many consumer products and grants researchers access to the raw sensor data.

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Gait; walking; running; pedometry; motion analysis

1. Introduction

Increased sedentary behaviour in children [1] and adults [2] has become more prevalent in the last decades. This trend has contributed to the increase in obesity rates and its secondary effects such as diabetes. Many countries and health organisations [3] are recommending an increased time of physical activity. Other applications include monitoring older adults [4]. One strategy to increase physical activity is the use of personal activity monitors and step counters such as Fitbit and Jawbone [5]. These devices motivate the wearer to set activity goals while accounting for their progress.

Consumers are given a summary of their daily activity and shown trends over time. However, for a researcher or "prosumer," the raw data are needed for deeper analysis. Commercial devices (e.g. Fitbit, Apple Health and Actigraph) typically use proprietary hardware, software and algorithms. This prevents getting raw data from the device for processing using third-party methods. Furthermore, assessment of the accuracy of the devices is difficult as the step counting methods are hidden.

Fitbits, specifically the Fitbit One and Flex [6–10], and Actigraphs, specifically the GT3X + and GT1M [11–13], have been tested and validated for step counting in several studies. While walking on a treadmill, Fitbits have shown good accuracy [6]. These validation studies have focussed on participants walking at a *constant* speed on a treadmill with no gait transitions. However, when in real-world scenarios, with changing speed and cadence, they lose accuracy [7]. These wrist-worn devices tend to undercount steps at low speeds or over count other arm motion as steps. Furthermore, Fitbits and Apple Health split step count data into time blocks of several minutes or hours. For a user looking at their daily totals, this bundling of data is fine. However, in a laboratory setting, this makes it difficult to distinguish step counts in discrete trials. These devices do not give the raw sensor data and must be used with proprietary software. The

CONTACT Joseph Michael Mahoney jmm694@psu.edu The Pennsylvania State University, Reading, PA 19610, USA

algorithms and methods to detect steps are not openly available. Raw data are available from the Actigraph through their software and a third-party extractor. However, the Actigraph is expensive at over $250 (depending on model) and another $1700 for analysis software.

Instead of relying on commercial devices, researchers can develop their own counting and activity devices using open-source hardware and software. This allows access to the raw sensor data but the data need to be processed to count the steps. Accelerometers [14–17] and gyroscopes [18], and inertial measurement devices (IMUs) [19] have been used successfully as sensor options. Deploying custom-made hardware for large-scale data collection is difficult for a research lab. One remedy is using the smartphone [20–22] that most subjects already have. Smartphones are typically already equipped with three-axis accelerometers and gyroscopes. Previous works have developed step counting algorithms for smartphones which utilise the accelerometer signals for counting steps using zero-crossings [23], peak detection and autocorrelations [20], and a comparison of all three of these techniques [24].

While these IMU-based methods of step counting are convenient and wearable, they all show error in measurement especially prevalent at "low" or "high" constant speeds and varying speeds [25]. To experimentally test new algorithms and hardware for counting steps, the true value must first be found. Manually and redundantly counting steps in real time or in video is the most accurate method to obtain the true value. However, this is time consuming for analysts to perform. Additionally, it can still be prone to errors from miscounting.

Footswitches offer high accuracy at counting steps but require specialised hardware put into the shoe [26]. Commercial footswitch and heel switch systems can cost hundreds of dollars and multiple sets may be needed to fit different shoe sizes.

There are several options for marker-based and markerless optical systems that can be used for step counting. At the high end are Vicon or Motion Analysis systems. These systems can be very expensive, require specialised training to use and need space to operate. Commercial systems like Dartfish [27] can track joint angles in real time, and thus be used to track steps. These systems require licencing and may be more complicated than needed for simple step counting. Software for the Microsoft Kinect™ has been used for markerless tracking of body segments [28,29]. The accuracy of these systems is not in question, but they have drawbacks in price, training or complication. Furthermore, most are not open source and customisable. Additionally, there is a gap in the literature for validating their ability to directly count steps.

Here, an optical system is presented for extremely accurate step counting in a controlled volume. The system uses off-the-shelf cameras and open-source algorithms for the analysis. The transparency of the systems allows for customisation and extension. The optical system's camera (at the time of purchase) was $300. It is shown that the system works at standard and high-definitions and high and low frame rate and therefore not limited to use on the tested cameras. The method is validated against human subjects walking at constant- and varying speeds on a treadmill. The reliability of the method is shown to be very good and could be used as the "true count" when comparing future counting methods, such as those from IMUs, without having to manually count steps during or after an experiment. This automation allows for larger sample sizes and longer sampling times without having to allocate time to manually count. Furthermore, the marker identification method can be extended for future applications.

2. Methods

The automated step counting method is presented here. The details of the method are described in Section 2.1 and validated using human subject trials explained in Section 2.2 using statistical methods in Section 2.3.

2.1. Video marker tracking

The step-counting method utilises image processing on video taken from optical cameras. Video of the subject in the sagittal plane was captured by an off-the-shelf consumer-grade Canon camera. Though only one camera is required for the analysis, two cameras were used simultaneously for quality comparison purposes. A Canon r500 captured video at its highest quality setting, 1920×1080 and 60 fps (referred to as cam60), and a Canon r400 captured video at its lowest quality setting, 1280×720 and 30 fps (referred to as cam30). The lower resolution and frame rate should provide faster processing but may be inaccurate at higher walking speeds. A green marker (a craft pom pom) was affixed to the treadmill and another near the fifth metatarsal of the subject's left foot. A custom

Matlab (R2018a, Natick MA) script [30] was created to analyse the video to count the number of steps.

To process the video, the analyst first selects the recorded file. A static image of the first frame of the video is displayed and they are asked to select a region of interest to crop the video. This reduced area (Figure 1, Top) decreases visual artefacts and increases the processing speed. The analyst then identifies the treadmill marker and the foot marker by clicking them on the static image. The two markers' RGB (red, green, blue) colours are found, averaged and stored as the marker colour. Next, the ℓ^2-norm is calculated between the RGB values of every pixel in the frame and the stored marker colour (R_0, G_0, B_0). This distance matrix, d, is calculated by Equation (1).

$$d = \sqrt{(R-R_0)^2 + (G-G_0)^2 + (B-B_0)^2}, \qquad (1)$$

where R, G, B are the *matrix* red, green, blue values from the frame of video. The image is converted to binary by setting any pixel with a d-value below a set threshold to white (identified as a marker: one in the matrix) and otherwise set to black (identified as not a marker: zero in the matrix). For this testing, the threshold was set to 50. A *k-means* cluster analysis [31] is run on the now-binary matrix. As there are only two markers in the frame, the routine seeks the two centroids of the marker groups. The initial coordinates the user selected are used as the starting point for the centroid locations. The coordinates of the two centroids are identified and stored. Figure 1(Bottom) shows the thresholded binary image and the calculated centroid locations. The second frame in the video is imported into an RGB image and thresholded using the same values as the first frame. The centroids of the markers in this frame are identified using the *k-means* with the previous centroids as the starting point of the search. This process repeats for all subsequent frames using the previous frame as the start point of the search.

Now, having the coordinates of the centroids of the markers for every frame, the horizontal distance between the markers is calculated. These values were zero-lag filtered using a fourth-order low pass Butterworth filter with an 8 Hz cutoff frequency. The typical horizontal distance is a periodic wave as shown in Figure 2. The peaks of the distance values (where the foot is farthest from the back of the treadmill) are found using Matlab's FINDPEAKS function. These peak values are located near heel strike of the left foot [32] and, thus, the number of identified peaks will match the number of steps taken. For this paper, a "step" is defined as each time the *left* foot hits the ground.

2.2. Experimental validation

Fifteen subjects (μ [σ]: age 20.2 [3.8] years; height 1.7 [0.1] m; mass 71.2 [10.9] kg; BMI 23.9 [3.4] kg/m^2) were recruited to validate the automated step counting method. Subjects walked on a motorised treadmill (Quinton TM55, Mortara, Milwaukee WI) under four conditions: 1.21 (walk), 2.01 (jog), 2.68 (run) m/s and ramping speeds up and down (vary) between 1.21 and 2.68 m/s. For each condition, the subject walked for 90 s. The "jog" speed was set to be a velocity near a typical walk-run transition while "run" was set to a velocity that is typically running [33]. However, subjects were not instructed to employ a specific gait

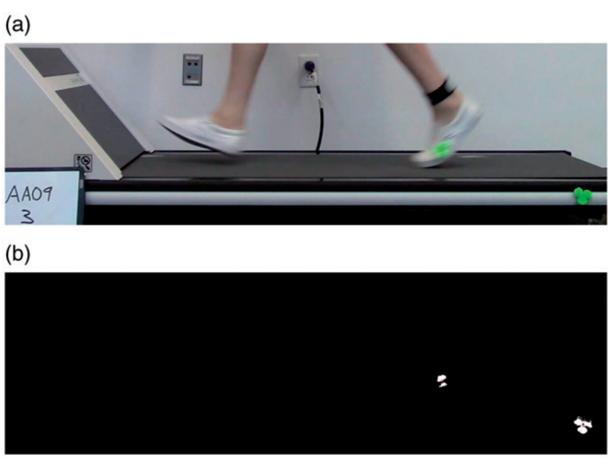

Figure 1. Top: Cropped Video Image. Green marker clusters are placed on treadmill and fifth metatarsal of left foot. Bottom: Thresholded Image. Pixels identified as "marker" are white. Centroids (found by the *k-means* routine) of the two markers are shown as red "x".

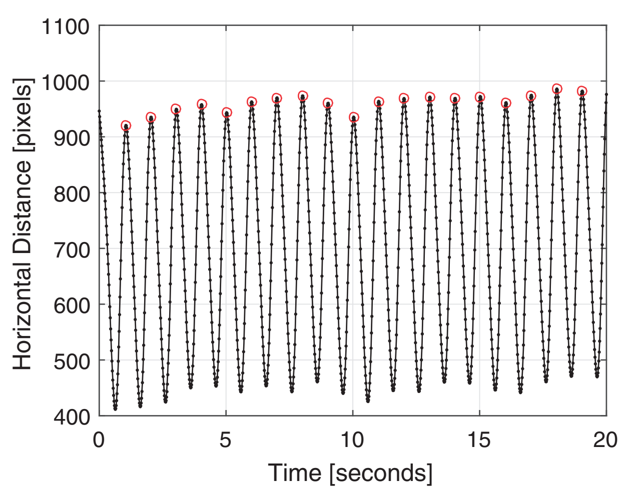

Figure 2. Typical video output of horizontal distance between centroids. For visual clarity, only 20 s is displayed. Red circles indicate the automatically-found peaks. Total number of peaks counted as the total number of left foot heel strikes.

style at any speed. The presentation order was randomised for each subject. Data collection was performed with permission of the Pennsylvania State University Institutional Review Board.

A computer macro (AutoHotkey) controlled the starting and stopping of data collection. Each 90-s trial began when the computer sent an audio pulse to the two cameras. When the 90 s elapsed, a second audio pulse was sent. The recording between these pulses serves as the 90 s for all manual and automated analyses. This method ensures consistency between the video data so that the comparison is one-to-one. Subjects were given approximately 60 s on the "jog" speed to acclimate to the treadmill before the first data collection began. They were given approximately 60 s between trials to rest. Subjects walked with a marker affixed to the left foot near the fifth metatarsal. The cameras were placed about ten feet from the treadmill.

Each video was visually assessed by two analysts and the number of heel strikes of the left foot between audio pulses was recorded. Counting steps from the video ensured that the exact same time span was being assessed between the computer and analysts. The average count of the analysts was used and serves as the "gold standard" of step count. The video was then automatically assessed by the method described in Section 2.1. The analysis codes ran identically on all video data. The percent relative error for each camera configuration (i.e. cam30 or cam60) was calculated using

$$error = 100\left|\frac{devicecount - manualcount}{manualcount}\right|$$

2.3. Statistical methods

Bland–Altman plots [34] were created for each camera configuration to evaluate their absolute agreement with the true step count.

Intra-class correlation (ICC) analysis, using ICC(2,1) [35–37], was performed on the step counts from each camera configuration paired with the manual count to find the degree of absolute agreement. All measures are based on a single observation per trial except for the manual count which is the average of two counts by independent investigators. However, for a more conservative estimate, ICC(2,1) was used over ICC(2,k). Trials were partitioned by condition. For this ICC comparison, the significance threshold was set *a priori* to $p = 0.0063 = 0.05/8$ using $\alpha = 0.05$ with eight pairings of configurations and conditions. The statistical analysis was performed in Matlab and utilised ICC code by [38].

A plot of the interaction between condition and camera configuration is shown in Figure 4. Because of

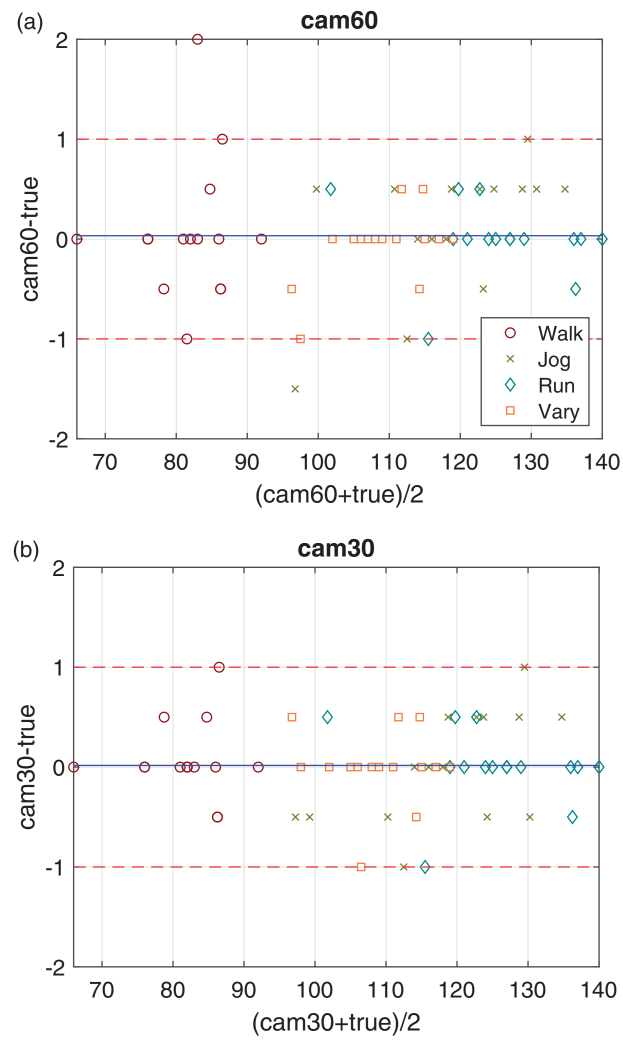

Figure 3. Bland–Altman Plots. The blue line indicates the mean difference in step counts while the red-dashed lines indicate 95% limits of agreement. Limits were calculated using the 2.5th and 97.5th percentiles of the experimental data. 95% of the counts are one or fewer off from the true value.

the interaction effect, sample size less than thirty, and non-normal distributions, the median relative error was compared between configurations using a Friedman test [39] (rather than an ANOVA) using condition as the blocking factor. This test controlled for the effect of condition on the error for each configuration. For this comparison, the significance threshold was set *a priori* to $p = 0.05$. To compare the accuracy between the two cameras, a confidence interval of the mean difference in step count was created. Because the counts were discrete, bootstrapping was used with 5 million paired samples.

3. Results

Bland–Altman plots for each camera configuration are provided in Figure 3 to evaluate their absolute accuracy. For both cameras, 95% of the trials fell within one step of the true value. The absolute accuracy is unchanged as more steps were present in the trial. No systematic error was observed with the configurations.

The ICC(2,1) measurement results for each camera configuration and condition are displayed in Table 1.

A plot of the interaction between condition and camera configuration is shown in Figure 4. Qualitatively, there appears to be a small interaction effect between the condition and camera configuration at the lowest tested speed. The relative error of each camera configuration (pooled among conditions) is shown as a boxplot in Figure 5. The median relative error for each camera configuration was 0%. The error distributions are not normally distributed, nor symmetric about the median. Because of the interaction effect and the non-normal distributions, the median relative error between configurations was compared using a Friedman test using condition as the blocking factor. This test controlled for the effect of condition on the error for each configuration. For this comparison, the significance threshold was set *a priori* to $p = 0.05$. No significant difference in the medians was observed between the camera configurations ($p = 0.55 \gg 0.05$).

Though no statistically significant difference was found, further analysis was conducted to quantify any difference between the configurations. Using bootstrapping, the 95% confidence interval between the mean count difference between camera configurations was found to be [−0.1, 0.15] steps. These values reached convergence using the 5 million samples.

4. Discussion

The total step count from the optical system in both configurations had excellent absolute agreement ICC(2,1) >0.98) with the manual count. There was no statistical difference detected in the accuracy of the lower quality setting (cam30) compared to the higher quality setting (cam60) as shown by the failure of the Friedman test. Furthermore, the mean difference between the configurations was shown to be less than a step using the bootstrapped comparison. It was anticipated, especially at higher ambulation speeds, that the lower frame rate would perform worse. Because the highest movement speed for this experiment was 2.68 m/s, this loss of quality may have not yet been observed. There was an appreciable difference, however, in the computation speed of the video analysis. On the same computer, the cam60 analysis took an average of 3.83 s per second of video while the cam30 analysis took 1.0 s/s. Additionally, the cam60 video files were about ten times the size of the cam30 files.

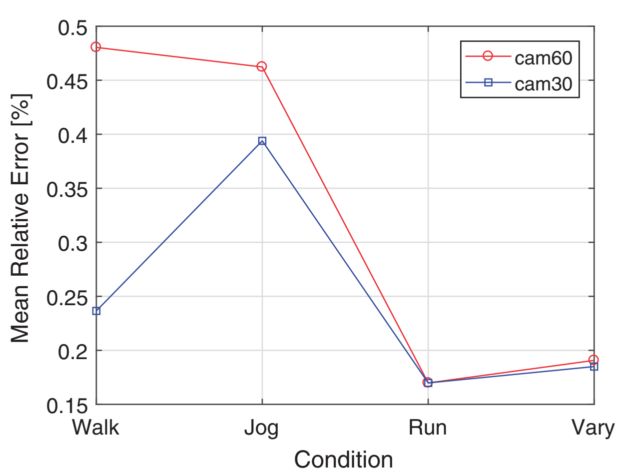

Figure 4. Interaction diagram. Visually, the accuracy becomes slightly worse for cam60 and the slower speeds.

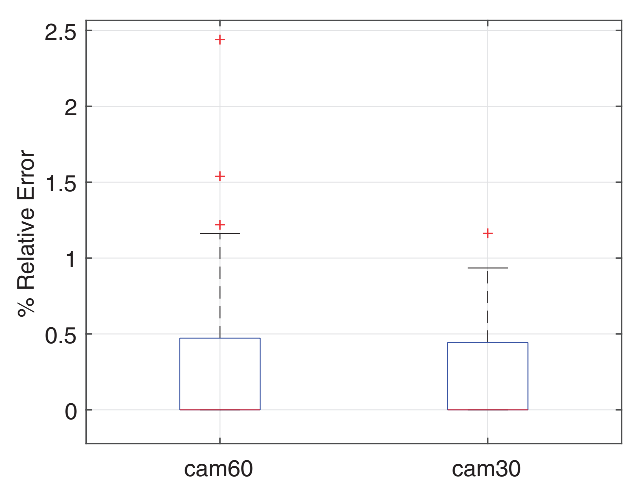

Figure 5. Boxplot of the relative error of the devices. For each device, all trials across conditions are pooled. By a Friedman test, there was no significant difference in medians between the two camera systems.

Table 1. ICC Results from method comparison. All ICC(2,1) [95% CI] comparisons are made with the manual count. All values have $p \ll 0.0063$ and have been rounded to three digits of precision.

Method	Walk	Jog	Run	Vary
cam60	0.994 [0.982, 0.998]	0.998 [0.995, 0.999]	0.999 [0.998, 1.00]	0.999 [0.996, 1.00]
cam30	0.998 [0.995, 0.999]	0.999 [0.996, 1.00]	0.999 [0.998, 1.00]	0.999 [0.996, 0.999]

The variable speed condition tested the ability of the analysis method to count step correctly during gait transitions. At constant speed, using Fourier Analysis on accelerometer or gyroscope data or a calculation using stride length has been shown to be reliable methods [12,20]. However, at varying speed, these methods will likely not work as they rely on the stationarity of the signal. Wavelet analysis may give a more accurate count at varying speeds and gait transitions [15].

5. Conclusions

Both optical step counting camera configurations were shown to be accurate over the tested range of walking and running speeds. Furthermore, they were robust to gait transitions during a trial. The positive results from the varying-speed trial give hope for their utility for counting steps during free walking.

The optical system demonstrated near-perfect agreement with the manual count at all tested conditions for both quality settings. Additionally, no difference in accuracy was detected *between* the higher and lower quality settings of the cameras. The lower quality setting has the benefits of running the analysis in a third of the time and the files occupying one-tenth of the disk space compared to the high-quality setting. The system worked with constant walking and running gait as well as transitioning between them during a trial. These methods were effective for treadmill walking.

The optical system can be expanded to limited overground walking by moving a single camera back and having subjects walk sagittally to the camera. This will allow for a larger capture volume and not restrict subjects to treadmill walking. The marker detection algorithm can be extended to more advanced applications. For example, being able to track the centroids of multiple markers in a frame can allow for tracking of the position and angle of individual limbs and then the joint angle between them. This will allow for a low-cost kinematic motion capture. Finally, multiple cameras could be synchronised to capture bilateral motion.

Currently, the computer processing time for the optical systems is fairly high (especially for the HD quality). However, it takes only a few seconds for an analyst to initiate before the process is automated. The efficiency of the programming can likely be improved and, in the future, reworked for an open source language such as Python. These improvements will also allow for greater accessibility to clinicians and groups without a Matlab licence. This study did have a limited upper range of speed that was tested. Further validation will be needed for true running speeds.

The lack of accuracy difference between the high and low-quality settings on the camera shows that the analysis could be done on video taken from most digital video cameras, including smartphone cameras. With no need for specialised cameras and near-free markers, the system is portable and affordable. Data can be captured in remote locations and processed later. With a recoding of the analysis software, the system will be easily deployable in clinical, academic and home environments.

Disclosure statement

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ORCID

Joseph M. Mahoney http://orcid.org/0000-0002-8098-0170
Matthew B. Rhudy http://orcid.org/0000-0001-7613-4003

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