A New Dataset for Evaluating Pedometer Performance

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***Abstract*—This work describes a new dataset to improve pedometer evaluation. Prior evaluation techniques focus on regular gaits using laboratory assessment to simplify the manual counting of actual steps. Our goal is to analyze pedometer algorithms under more natural conditions that occur during daily living where gaits are frequently changing or remain regular for only brief periods of time. We video recorded 30 participants performing 3 activities: walking around a track, walking through a building, and moving around a room. Walking around a track uses a regular, consistent gait, and represents the traditional approach to pedometer evaluation. Walking through a building and around a room are activities that include varying amounts of pauses and gait changes, and represent a wider variety of normal daily activities. The ground truth time of each step was manually marked in the accelerometer signals by observing the videos. Collectively 60,853 steps were recorded and annotated. A subclass of steps called shifts were identified as those occurring at the beginning and end of regular strides, during gait changes, and during pivots changing the direction of motion. While shifts comprised only .03% of steps in the regular stride activity, they comprised 10-25% of steps in the semi-regular and unstructured activities. We believe these motions should be identified separately, as they provide different accelerometer signals, and likely result in different amounts of energy expenditure. The proposed dataset will be the first to specifically allow for pedometer algorithms to be evaluated on unstructured gaits that more closely model natural activities.**

I. Introduction

This paper considers the problem of assessing pedometer accuracy. A pedometer is a portable device worn or carried by a person that counts each step taken. Pedometers typically detect steps by measuring motion through use of an accelerometer. The accuracy of a pedometer is a measure of the number of steps reported by the device compared to the number of steps taken by the wearer. Pedometer accuracy has been shown to vary based on the location the sensor is worn on the body [10], [14] and the pace (rate of motion) of the wearer [4], [6], but differing gaits (ex: walking, running, climbing stairs) have not been as extensively evaluated. There is currently no established gold standard for evaluating pedometer accuracy.

Pedometer accuracy has primarily been evaluated in a laboratory setting due to the challenges in measuring ground truth step count. Laboratory studies use a treadmill where an experimenter or stationary camera can observe a subject walking to directly count steps [3], [4], [7]. Outside the laboratory, studies of accuracy compare step counts of multiple pedometers worn concurrently [5], [12], [14]. The assumption is that the pedometer used to collect a reference step count is presumed to be accurate based on results from previous laboratory trials [12]. However, this type of bootstrapping assumes the accuracy of the reference pedometer that was established in the laboratory will be the same during natural daily living. In addition, pedometer step counts are only evaluated against a tally of the steps taken over a designated period of time. For algorithm development and assessment, it would be preferable to also provide the exact times at which steps occur so they could be individually assessed.

Pedometer accuracy has been shown to vary when the pace of the wearer becomes slower or faster than a moderate walking rate [4], [5], [9], [10], [15], but changes in gait have not been as extensively studied. Some studies have evaluated pedometers across regular gaits, including walking, climbing stairs, and running, but gaits which are interrupted by pivots, shuffle steps, or brief pauses have not been evaluated. Akahori et. al. evaluated accuracy for walking and climbing stairs, but excluded beginning and ending steps and transitions between activities [1]. Jayalath et. al. have shown varied accuracies for pedometers worn while participants walk, climb stairs, and walk up or down an inclined plane [6]. Zhong et. al. examine walking, running, and climbing stairs, and detected transitions between these activities, but performed the study on only two participants [19]. Lu et. al. combine an accelerometer, gyroscope, and pressure pad to identify when participants were sitting, walking, running, or biking, but only reported step counting accuracy for the walking condition [8]. There is no standard for evaluating pedometer accuracy across varying gaits, and for the transitions that occur between periods of regular gait.

Pedometer accuracy has also been shown to vary depending on the location on which the sensor is worn [11]. Pedometers are worn on a variety of locations based on personal preference. In each location, steps will produce a different accelerometer signal, so pedometer algorithms developed for one location will likely not translate well to another position. Sheu et. al. evaluated their pedometer algorithm at three different locations (waist, pocket, and in a backpack), but wrist and ankle were not studied [13]. Some studies developed algorithms to detect the position at which the sensor was worn but do not count steps [11], [17]. Tang et. al. developed an

978-1-5090-3050-7/17/$31.00

algorithm to detect sensor location and count steps for walking and running, but locations were all limited to sites located near the hip or wrist (trousers front and back pockets, coat pocket, hand held, and in a handbag) and did not asses the ankle [16]. Park et. al. found that waist, chest, and armbands produced accurate step counts, but keeping pedometers in a purse or pocket produced less accurate tallies [10]. Silcott et. al. examined pedometer accuracy when worn on the belt, in a pocket, or in a lanyard around the next and found that accuracy varied depending on location worn [14].

This work describes a new dataset designed to allow pedometer algorithm evaluation on unstructured gaits in natural settings. Three activities, each designed to approximate a different type of motion expected during daily living, were performed by 30 participants, yielding approximately 60,000 steps. Each participant's lower extremities were video recorded and each recording was manually reviewed to provide the specific times at which steps occur. Each participant wore sensors on the wrist, hip, and ankle so algorithms can be developed and evaluated for multiple locations. We believe the described dataset could further pedometer algorithm development by expanding evaluation to include unstructured gaits and providing a standardized dataset that includes variations in activity, gait and body location.

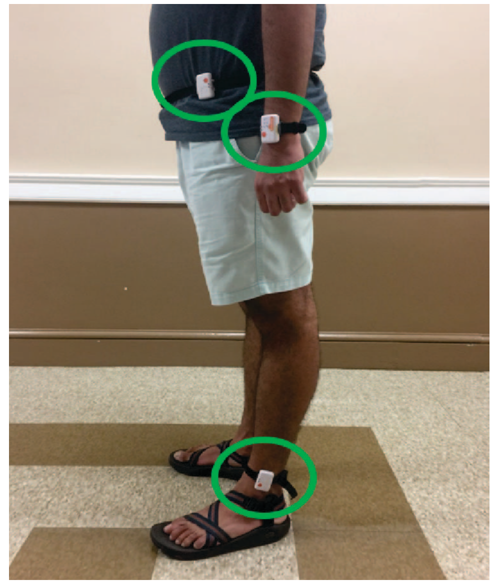

Fig. 1. Locations where sensors were worn. For this right-handed participant, sensors are worn on the left wrist, hip, and left ankle.

II. Methods

The experiment described in this study was conducted at Clemson University, behind Cooper Library and within Riggs Hall. Thirty participants were recruited to participate in the study, including fifteen males and fifteen females. Participants were recruited via email and provided a $20 Amazon gift card for their participation. Each subject provided informed consent, filled out a Physical Activity and Readiness Questionnaire (PAR-Q) [2], and provided height, weight, and gender information. The study was approved by the Clemson University Institutional Review Board for the protection of human subjects (IRB Number: IRB2017-048).

Each participant wore three Shimmer3 sensors. Participants were instructed to position each device on their non-dominant wrist, hip, and non-dominant ankle, and they were instructed to position the device however they would naturally wear an activity monitor at each location, as shown in Figure 1. Each sensor recorded accelerometer and gyroscope data at 15 Hz. The accelerometers were set to record from -2 to 2 gravities and gyroscopes from -250 to 250 degrees per second.

We designed activities to model walking patterns of typical daily life. We divided typical walking patterns into three categories: exercise, moving around a building, and moving around a room. Exercise typically involves a period of repetitive motion such as walking on a treadmill, walking around a track, or walking down a road. Moving around a building typically involves multiple periods of shorter duration movement, as when walking from one room to another, interspersed with periods of moving about each room. This could also include periods of walking up or down stairs. Examples include walking to a meeting from an office or walking to a classroom for a lecture. Moving around a room typically involves very brief periods of walking interspersed with periods of time in which significant motion occurs but no steps are taken. Examples of this include cooking, folding and putting away laundry, or cleaning the house. We refer to these walking patterns as regular (exercise), semi-regular (moving around a building), and unstructured (moving around a room).

Each participant was asked to perform three activities, each designed to elicit one of the walking patterns described above. In the regular gait experiment, the participant was instructed to walk two laps around a designated path at their normal walking pace. In the semi-regular gait experiment, participants were instructed to perform a scavenger hunt, locating four objects in four different rooms throughout a building. The unstructured gait experiment required participants to build a small Lego toy by assembling pieces distributed among 12 small bins around a room. Participants were only allowed to gather one bin of pieces at a time and constructed the Lego at a central location. This pattern simulates preparing a meal in a kitchen. Each of these activities was designed to take approximately 10 minutes to complete.

Throughout each of these activities, participants' lower extremities were recorded through use of an iPhone 4 camera by having an experimenter follow the participant through each activity as shown in Figure 2. The camera records with a resolution of 720p with a frame rate of 30 fps and, when directed at the participant's lower extremities, produces recordings as shown in Figure 3. These recordings were later reviewed to manually annotate each step taken for all participants. The sensor data from the Shimmer3 devices were synchronized to the video recordings so the manually annotated steps could be located in the accelerometer and gyroscope data. Steps were annotated based on observation of the recorded video, and the

Fig. 2. The procedure used to record steps from each participant. The researcher followed the participant and recorded their lower extremities throughout each experiment.

Fig. 3. The view from the iPhone used by the experimenter. Only lower extremities were recorded in order to protect participants' identities.

foot used to take the step was specified. Steps were marked when the toe came in contact with the ground.

The tool developed for the evaluation process is shown in Figure 4. In this image, nine accelerometer signals are shown, with time represented horizontally and the magnitude of each accelerometer signal displayed vertically. The top row of data corresponds to the x-axis of the wrist signal, followed by the y- and z-axes for the wrist. This pattern is repeated for the hip data (rows 4-6) and the ankle data (rows 7-9). A menu option allows the researcher to display each sensor on its own, providing a magnified view of the three axes for the desired sensor. The time axis can also be zoomed in or out to show local details or a broader view of the signals over longer periods of time.

The specific data for the current index being examined is shown textually. The actual value (in gravities) of each accelerometer signal is displayed in the top left of the screen. The current data index and the time from the start of the recording are also indicated at the top of the screen, and the current index is marked with a green rectangle on each of the data signals. The current frame of the video is shown on the right. The sensor or sensors currently being observed are displayed below the video image. Keyboard shortcuts can be used to move ahead or backwards one frame at a time or one second at a time. A GUI in the top right of the screen can be used to jump to any specified index.

III. Results

The manual annotation process took approximately 4 hours per participant for a total of 120 hours of annotation. A total of 60,853 steps were annotated. The annotation process revealed that steps could be categorized into two distinct groups, which we call steps and shifts. In the regular gait activity, because the motion of walking is repetitive and uninterrupted, each step taken can be clearly counted and evaluated. Virtually all steps in the regular gait activity can be defined by the inclusion of three elements: 1) the foot moves, 2) the body weight shifts in the direction of the foot movement, and 3) the action takes place within a repeating pattern. An activity meeting these criteria is called a step. While steps do occur within the semi-regular and unstructured gaits, a significant number of motions occur which contain a foot movement, may or may not include a weight shift, and are not within a repeating pattern. We call this second type of motion a shift. Shifts are identified most frequently when one of three different movements occur: 1) the first or last stride in a sequence of steps, 2) shuffles (weight shifts accompanied by small foot movements), and 3) pivots (one foot rotates while the other is planted). Shifts have a different appearance in the accelerometer signal and we expect shifts to produce a different level of energy expenditure when compared to traditional steps.

In Figure 5, 15 steps are shown during the regular gait activity, and in Figure 6, the common situations in which shifts occur are shown. The top segment of data shown in Figure 6 demonstrates a shift that begins a sequence of steps. The second segment of data demonstrates a shift which ends a sequence of steps. The third segment of data shows a pivot, which occurs as the participant changes direction. The bottom segment of data shows a weight shift. Each type of shift has a smaller magnitude and is generally more isolated than a step. These differences are critical for detection because typical pedometer algorithms detect steps by identifying a repeating pattern of zero crossings at regular intervals. Zero crossings typically require accelerometer signals to exceed a threshold, as determined by autocorrelation of the surrounding signal. Because shifts have smaller magnitude than steps, they are less likely to exceed the threshold required for detection. In addition, most pedometer algorithms look for several consecutive zero crossings at regular intervals in order to identify steps. The temporal isolation of shifts could also contribute to inaccurate detections.

The summary statistics for the dataset can be found in Table I. Each activity was standardized based on expected completion time (approximately 10 minutes for each), so the

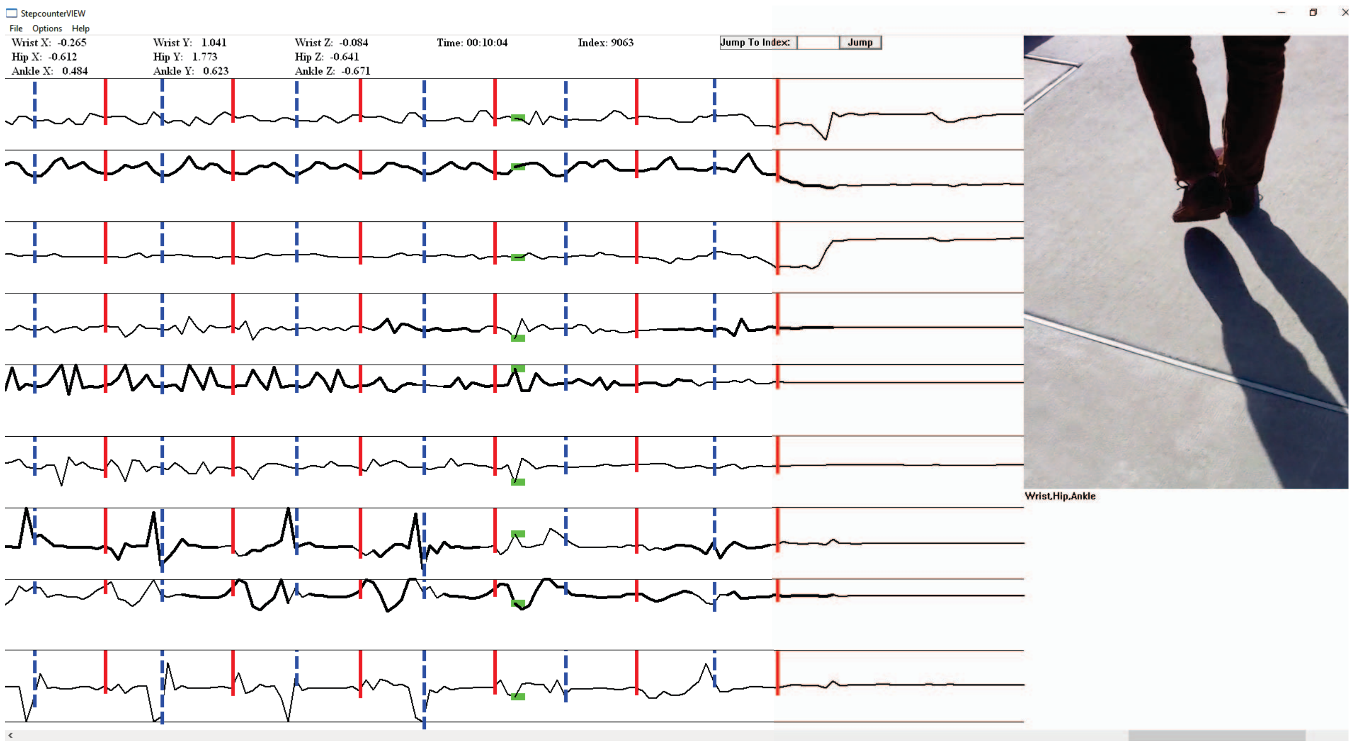

Fig. 4. The tool used to mark each individual step based on video recording. Steps with the right foot are indicated with solid red lines and steps with the left foot are indicated with dashed blue lines.

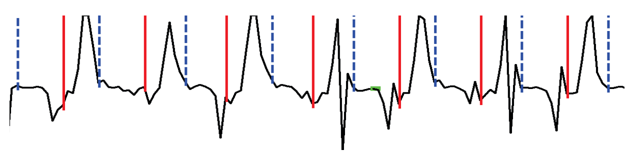

Fig. 5. Shows one axis from the ankle accelerometer from the regular gait activity.

TABLE I
SUMMARY OF STEPS AND TRANSITIONS MANUALLY RECORDED THROUGH EACH OF THE THREE ACTIVITIES.

Experiment	Steps	Shifts
Regular	31,447 (99.7%)	88 (0.03%)
Semi-regular	19,919 (89.6%)	2,317 (10.4%)
Unstructured	5,263 (74.3%)	1,819 (25.7%)
Overall	56,629 (93.1%)	4,224 (6.9%)

number of steps taken in each exercise vary. An average of 1,050 steps were taken in the regular experiment, 667 in the semi-regular experiment, and 175 in the unstructured experiment. Very few shifts occur in the regular gait activity, and these are primarily limited to the first and last strides taken by each participant. In the semi-regular activity, shifts compose 10.4% of all manual annotations. In the unstructured gait activity, shifts compose 25.7% of all manual annotations. As the gait becomes more interrupted and less repetitious, the percentage of shifts increases.

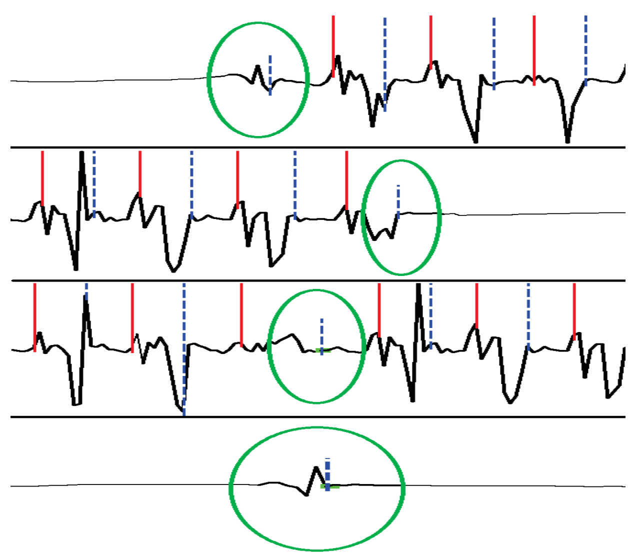

Fig. 6. Depicts the common shifts seen in the semi-regular and unstructured activities. The top data segment shows a shift which initiates a sequence of steps. The second data segment shows a shift ending a sequence of steps. The third data segment shows a pivot. The fourth data segment shows a weight shift.

IV. Conclusion

Studies designed to develop pedometer algorithms from accelerometer and gyroscope data lack a gold standard for evaluation. Laboratory studies do not necessarily represent natural daily living. Prior real world studies evaluate accuracy by comparing step counts between multiple pedometers worn concurrently. Video recording will allow for more accurate assessment of pedometer algorithms on realistic gaits, although it does require significant time to manually annotate (in our experiment, 4 hours per participant). The proposed dataset will be the first to specifically allow for pedometer algorithms to be evaluated on unstructured gaits that more closely model natural activities.

We believe the ability to study unstructured gaits will provide opportunities for both physiological studies, which seek to assess commercial pedometer accuracy, and engineering studies, which seek to develop new pedometer algorithms. Physiological studies, which focus primarily on evaluating commercial devices, could adopt a video recording strategy to improve the ability to assess commercial pedometers in natural conditions. In addition, it is possible that a commercial pedometer's inability to detect and count what we call shifts (steps not occuring during a regular gait) could contribute to pedometer performance differences. Engineering studies seeking to develop improved pedometer algorithms can consider identification of shifts in addition to steps. Successfully identifying shifts should improve pedometer accuracy and allow better assessment of energy expenditure during daily living.

While the proposed dataset will improve pedometer evaluation in naturalistic conditions, it does have limitations. The dataset considers motions consistent with exercise, walking through a building, and walking through a room, but other activities may fall outside or between these patterns. Additional studies compiling additional gaits could be added in the future. Sensors were only worn on the wrist, hip, and ankle. Additional locations could be used, such as in a pocket, in a bag, or attached to a shirt. Participants were instructed to position the devices naturally at each location, so the orientation of each sensor can vary for each participant. This is a limitation, but also an advantage because it simulates more realistic usage (people wear pedometers at many locations and orientations). Future work will also include investigations into the differences between step and shift signal appearances, their detectability, and energy expenditure evaluation.

In conclusion, this study provides a dataset developed for the evaluation of pedometer algorithms in natural conditions, using video to provide accurate step counts. The dataset allows pedometer algorithms to be evaluated across multiple sensor locations (wrist, hip, and ankle) and gaits. The gaits recorded included realistic, aperiodic motions, in addition to the regular, consistent motions examined in traditional pedometer studies. The evaluation process revealed that two types of motion, steps and shifts, should be evaluated separately. The dataset includes roughly 60,000 video recorded steps which can be used for future evaluation.

Acknowledgment

The work in this paper is supported by a Brooks Sports Science Institute grant.

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