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WeAllWalk: An Annotated Data Set of Inertial Sensor Time Series from Blind Walkers

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ABSTRACT
We introduce WeAllWalk, a data set of inertial sensor time series collected from blind walkers using a long cane or a guide dog. Blind participants walked through fairly long and complex indoor routes that included obstacles to be avoided and doors to be opened. Inertial data was recorded by two iPhone 6s carried by our participants in their pockets and carefully annotated. Ground truth heel strike times were measured by two small inertial sensor units clipped to the participants' shoes. We also show comparative examples of application of step counting and turn detection algorithms to selected data from WeAllWalk.

CCS Concepts
• Human-centered computing→ Ubiquitous and mobile computing→ Ubiquitous and mobile devices • Human-centered computing→ Accessibility→ Accessibility technologies

Keywords
Inertial sensing; Wayfinding; Step counting.

1. INTRODUCTION
For someone who cannot see, tasks such as finding one's own location or figuring out how to reach a certain location in a building can be daunting, especially if this person is not familiar with the building layout or if he or she has poor orientation skills. Lacking access to visual landmarks, a blind traveler can quickly become disoriented; and if he or she at some point finds himself or herself being lost, tracing back their own steps can be equally challenging. For this reason, many blind individuals do not visit new places (office buildings, hospitals, schools) without a sighted guide who can show them around and lead them to the desired destination. Without the ability to travel independently, people in this community may miss opportunities for education, employment, leisure, socialization, and participation.

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Personal navigation systems are designed to provide their users with spatial information and directions when traveling to new places. While outdoor navigation is to some extent already solved by the use of GPS, this is not an option for indoor navigation, and various technologies are being explored. Of course, systems for indoor navigation are useful not only for blind travelers: anyone may need directional information at times. Indeed, there is increasing commercial interest in technology that may help one locate a shop in a mall, a room in a building, or one's own car in a parking lot. Several research groups have started building assistive applications on top of this technology, adapting it to the particular needs of specific communities of users.

This contribution focuses on systems that support indoor wayfinding using dead reckoning from inertial sensors. This approach has the advantage that it requires no external infrastructure (as with iBeacons or similar technologies) or use of a camera (as with image-based technologies). Note that, until wearable cameras are socially accepted and widely used, users of a camera-based localization system would need to take pictures of the environment with their cell phone, something that for a blind person may be difficult and possibly awkward in social settings. In contrast, inertial sensing can be conducted with a smartphone conveniently tucked in one's pocket.

Dead reckoning uses data from the inertial sensors (and from magnetic sensors, when the data they produce is reliable) to estimate the trajectory taken by the user. In theory, data from a tri-axial accelerometer could be doubly integrated to obtain its location. In practice, this is only possible with sensors attached to the walker's feet; by detecting when one's foot is resting on the ground, it is possible to perform a zero velocity update, thus largely limiting errors due to drift. When the sensors are worn elsewhere on one's body or garments, a safer strategy is to use them for step counting[1], and to indirectly recover one's position using an estimated stride length, as well as orientation information from the gyroscope. Various versions of this approach have been used to track a person walking in a place with known geometry (obtained, for example, from a floor plan). Even when the geometry of the environment is not known, it is possible to use dead reckoning (e.g. by means of step counting and robust turn detection) to help a person re-trace a path taken in a building.

Step counting and turn detection with a smartphone placed in one's clothing can be computed reliably if one walks with a steady gait and in mostly rectilinear paths. Blind individuals,

[1] Note that many blind individuals prefer receiving information about distances in steps, rather than in feet or in time [21].

however, often exhibit body motion patterns during gait that are markedly different than those of sighted people [15] (e.g., due to “scuttling” [9]). In addition, cane users, who are trained to execute the 2-point touch or constant sliding technique [4], swing their cane-holding arm left and right, resulting in additional upper body rotation. As already observed by other authors [9], step counting may be difficult (or require specific parameter tuning) to work robustly with these individuals and for any smartphone placement. Likewise, blind individuals, especially when walking in large spaces, and unless they use a guide dog, do not always walk on straight paths with sharp and clearly detectable turns. Rather, they often veer involuntarily, and need to correct their path when they realize that they are getting close to a wall or an obstacle.

This paper introduces a new, openly accessible and annotated data set of inertial sensor time series collected from blind individuals walking through relatively long and complex paths in realistic conditions, and carrying two smartphones in different locations on their clothing. The primary purpose for creating this data set was to allow other researchers to benchmark their algorithms (step counting, turn detectors, or other) on a common ground. This follows the example of other similar data sets (described in Sec. 2.3), with the critical difference that our WeAllWalk data was obtained from blind walkers, using either a long cane or a guide dog. More important, this data set does not just contain measurements from people walking on a straight line, as in previous collections [5] [29]. Instead, our participants walked on multiple paths with different levels of complexity, including turns at 45, 90, and 180 degrees, as well as through doors that needed to be opened. While walking, our participants occasionally veered off the straight path, got caught in wall openings, and collided with obstacles. These events (which are faithfully recorded in the WeAllWalk data set) are to be expected when walking without sight. We carefully annotated our measurement time series, indicating the start and end time of each such event. In addition, we provide ground truth data in the form of heel strike times, measured by accessory inertial sensors clipped to the participants’ shoes. We believe that this annotated data is representative of typical situations encountered by blind walkers, and that it should be very useful for anyone who wants to test their dead reckoning algorithms in realistic scenarios.

This article is organized as follows: After the related work, presented in the next section, we introduce the WeAllWalk data set in Sec. 3. We describe the sensor platform, the paths and their characteristics; we introduce the participants to this study and the procedures that were followed, and our criteria to annotate the data collected. In Sec. 4, we present some simple results of automatic step counting and turn detection on this data. Sec. 5 has the conclusions. The WeAllWalk inertial sensor time series data set is available at **http://n2t.net/ark:/b7291/d1cc7g**. It is released under the terms of the Creative Commons Attribution license (CC-BY-4.0).

2. RELATED WORK

2.1 Indoor Navigation via Inertial Sensing

There has been increasing interest over the past decade in personal navigation systems that support users in determining their location and in finding a path to a desired destination. While outdoor localization can be obtained, at least with an accuracy of a few meters, via GPS, this is not possible indoors, where the GPS signal becomes too weak for detection. Indoor navigation represents the “last frontier,” with whole conferences devoted to this subject [16][18]. A variety of techniques have been proposed [10] for indoor localization, including radio-frequency triangulation [37], image-based recognition [22], Bluetooth beacons [27], visual markers placed in specific locations [7], and dead-reckoning using inertial sensors (see survey by Yang et al. [35]). The use of inertial sensors for blind indoor wayfinding has also been considered by several authors [6][8][9][23][28][30] [31][35].

2.2 Step Counting

Automatic step counting (e.g., for physical activity tracking) has received considerable attention by the research and industry world alike. Commercial pedometers use sensors that can be embedded in shoes (e.g., the Adidas Micropacers), in a smartwatch, in a smartphone, and attached to ankles or a belt. We refer the reader to [36] for a review of different sensing modalities for step counting and other physical activity monitoring. A variety of algorithms have been proposed for stride event detection from inertial sensor time series; an excellent review of some of the main algorithms is presented in [5]. Sensor placement certainly has a role in the characteristics of the data collected. For example, ankle or foot worn sensors usually provide more accurate step counting [13] than waist worn sensors. However, step counting accuracy does not seem to be greatly affected by the specific location of the sensor on other parts of the body [14][5] (including on head-mounted displays [3]).

Whereas the vast majority of step counting algorithms have been developed for able-bodied ambulators, some authors have addressed the performances of these algorithms with sensors

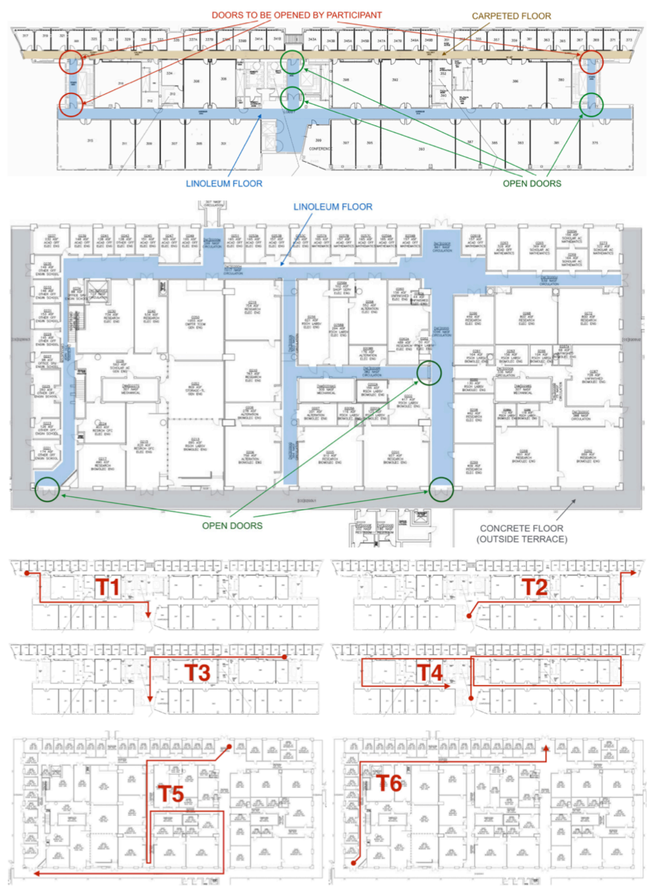


Figure 1. Top two rows: the floor plans of E2 and BE, respectively. Lower rows: the trajectories taken by our participants. T1–T4 were located in E2, T5-T6 in BE.

carried by people with some level of mobility impairment. For example, [25] evaluated different algorithms with ten mobility-impaired geriatric patients, while [38] designed and tested robust stride event detectors for users with Parkinson's disease. In both cases, participants carried an accelerometer on a belt around their waist. While none of the blind individuals who contributed to the WeAllWalk data set could be considered to have mobility impairment, use of a long cane or of a guide dog may result in a gait pattern that is quite different than for sighted walkers.

2.3 Similar Data Sets

We are aware of two existing openly accessible data sets with inertial time series collected from walkers carrying a smartphone; these data sets are briefly described below. Other similar data sets exist, but with different sensors and body placement (e.g., foot-mounted sensors [2]) which are not directly relevant to our intended use case.

The Walk Detection and Step Counting on Unconstrained Smartphones dataset [5] consists of time annotated sensor traces (accelerometer, gyroscope, and magnetometer) obtained from 27 participants walking a route at three different walking paces, and carrying one or two smartphones placed in various positions while walking.

The OU-ISIR Gait Database [29] consists of walking data from 744 participants wearing four sensors (three units with accelerometer and gyroscope, and one smartphone containing an accelerometer) located in a belt around the participants' waist. Participants walked on straight paths at varying inclinations.

WeAllWalk differs from these prior data sets in two main aspects. First, it contains data from blind walkers, both using a long cane and a guide dog. Second, the path traversed by our participants are much more complex and realistic than the straight routes considered in the previous data sets. The routes in WeAllWalk include turns at corridor junctions, active door openings, as well as sporadic stops or short re-routings due to involuntary collisions with objects or walls, as should be expected during regular blind ambulation. We carefully annotated the time series to identify intervals corresponding to walking in a straight line, taking a turn, or opening a door, as well as specific "features," such as when the walker stopped for a short moment, bumped into an obstacle or a wall, or deviated momentarily from the path, because for example, he or she missed a door or got stuck in an opening in the wall.

3. THE WEALLWALK DATA SET

3.1 Sensor Platform

3.1.1 Sensors

Our participants carried two smartphones (Apple iPhone 6), placed in different locations on their garments. Each smartphone recorded data from its tri-axial accelerometers, gyroscopes, and magnetometers. Data was sampled at a rate of 25 Hz. In addition, we recorded derived data produced by the iOS' Core Motion framework via proprietary sensor fusion algorithms. This derived data includes the estimated direction of the gravity force, the device's actual acceleration (obtained by subtracting the estimated gravity acceleration from the data measured by the accelerometer), the corrected magnetic field, and the device's attitude (the 3-D rotation of the device with respect to a static reference frame). Each data sample was time-stamped with the clock of the phone that originated it.

Figure 2. Examples of placement of the CPRO shoe-mounted sensor for ground truth step detection. The sensor is contained in the white small case, attached to a plastic padded clip.

In addition to the smartphones, our participants carried two small inertial sensor units clipped to their shoes (see Fig. 2). We would like to emphasize that we do not assume or expect that blind walkers would wear these shoe-mounted sensors in their daily life. These sensors were added for the sole purpose of enabling ground truth step counting (since placement at the foot level enables robust step detection [13]). Algorithms for step counting from inertial sensors in the smartphone can then be benchmarked against this ground truth data. We used MetaWear-CPRO[2] units, (shown in Fig. 2) which contain a 16-bit tri-axial accelerometer and gyroscope IMU from Bosch (BMI160). The accelerometers can work at a programmable range of ±2, ±4, ±8, or ±16g, whereas the gyroscope can work between ranges of ±125°/s, ±250°/s, ±500°/s, ±1000°/s, or ±2000°/s. For the experiments, we set the accelerometer range to ±2g, and the gyroscope range to ±500°/s. The inertial sensor time series measured by the shoe-mounted sensors (sampled at 25 Hz) are recorded together with data from the smartphones, and later processed to detect the ground truth heel strike times. Foot strike events for each foot are detected from these sensors using data from the Y-axis gyroscope (as in [32]) using a modified version of the UPTIME algorithm [1] (see Fig. 3).

All of the devices carried by our participants (two iPhone 6 and two foot-mounted sensors) are controlled via Bluetooth by a single iPhone 5 (called "control phone") carried by one of the experimenters. The system makes use of the Multipeer connectivity Framework to communicate between multiple iOS devices, and the MetaWear iOS Objective-C API to communicate with the MetaWear-CPRO sensors. The "control phone" is paired with each of the smartphones carried by the participant in order to broadcast commands to them, as well as receive status updates (e.g., acknowledgement that a command was received, battery life status from the MetaWear-CPRO sensors). The smartphones carried by the participant are then paired with each of the MetaWear-CPRO sensors, one per smartphone. This pairing is done remotely from the "control phone." Once the "control phone" is paired with the two smartphones carried by the participant, and each one of these is paired with a MetaWear CPRO sensor, the "control phone" broadcasts a series of commands. Some of these commands include starting and stopping the inertial sensors, synchronizing the smartphones and the MetaWear-CPRO sensors so that all sensor readings reference the same starting time, saving all the sensor data from the smartphones and the MetaWear-CPRO sensors, restarting the system for the next experiment, and more. All of this is done remotely and without having to physically interact with the smartphones carried by the participants during the experiment (e.g., having to take the smartphones out at the end of each trial in order to restart the system or save the data). All the sensor data from the MetaWear-CPRO sensors is streamed to the smartphone

[2] https://store.mbientlab.com/product/metawear-cpro/

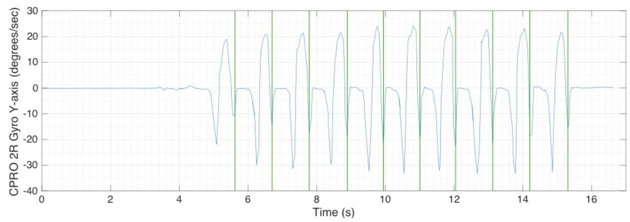


Figure 3. Time series of measurements from the Y axis gyro in the CPRO sensor clipped to one of our participants' right shoe during the calibration pre-trial. The green vertical lines represent heel strike times.

paired with and recorded along with all the sensor data produced by the iOS Core Motion framework.

3.1.2 Calibration Pre-Trial

Before starting to walk on the prescribed paths, each participant went through a "calibration" pre-trial, which consisted of walking along a straight corridor for twenty steps. The approximate time of each heel strike for each foot was recorded manually by an experimenter (by tapping on the screen of the control phone each time the participant placed a foot on the ground). This pre-trial phase is used to calibrate the parameters of the ground truth step detector from the shoe-mounted sensors described earlier (this calibration is performed off-line after data collection.) The ground-truth step detector is assumed to be well calibrated when the steps events it identifies correlate well with the steps that have been manually input by the experimenter. Note that the manual step input is performed only during pre-trial.

3.2 Paths

Our participants walked on 6 different paths in two different buildings in our campus (called the E2 and the BE building in this paper). The first paths (T1 to T4) are located in the E2 building, while the last two (T5 and T6) are located in the BE building. Floor maps of the buildings and the routes are shown in Fig. 1. Paths were all indoors and on level terrain (one path contained a stretch on an outdoor terrace). We decided against including staircases in the paths, due to safety concerns. Routes where chosen to have a variety of lengths and complexities. The shortest path was about 75 meters long and only included one 90 degrees turn; the longest path was about 300 meters long along an 8-shaped route, included seven turns and required the participant to open three doors. One path included a 180 degrees turn, while three paths included a 45 degree turn. The path order was designed in such a way that the end point of a path in the sequence corresponded to the start point of the next path.

Table 1. BLIND PARTICIPANTS LIST

ID	Mobility tool	Phone 1 placement	Phone 2 placement
P1	Cane Dog	Left breast pocket	Jacket right side pocket
P2	Cane	Jacket left side pocket	Tucked under shirt on right shoulder
P3	Cane	Pants left front pocket	Pants right back pocket
P4	Dog	Jacket left side pocket	Pants right back pocket
P5	Cane	Pants left front pocket	Pants right back pocket
P6	Cane	Holster clipped to front right belt	Pants left front pocket
P7	Cane	Jacket right side pocket	Pants left front pocket
P8	Cane Dog	Pants right front pocket	Pants left front pocket

For most of the time, participants walked in a corridor (with the width of the corridor varying from 120 cm to 210 cm), but some paths included traversal of an open space (an elevator hall or an entrance hall) as well as a passage next to a stairwell. In some cases, a turn was preceded or followed by a door that needed to be opened. In these cases, we informed the participant in advance of the presence of a door, and of whether the door had to be opened by pushing on a crowd bar, or be pulled open by a handle. In two places, the path went through a door that required substantial force for opening; in these cases, one experimenter opened the door for the participant.

Floor surface varied from industrial carpet to linoleum to rugged concrete (in the outside terrace). In addition, two industrial flat mats were placed in an elevator hall, and a metal plate was placed across a corridor. Some of our participants got their cane tip or their shoe briefly stuck at the edge of these floor coverings. Most environments were devoid of obstacles, although a few corridors contained large pillars, couches, chairs, tables, garbage bins, and obstacles in the form of appliances, which were kept on one side of the corridor. In these situations, we advised the participant to keep closer to the opposite side of the corridor. Some corridors contained openings to rooms or to other corridors, and a few participants occasionally moved close to these openings and got caught in the wall corner; this typically caused a short stop before the participant was able to get back to the intended route. At times, the participant also had to stop and move to the side to avoid walking into people who were standing in the corridor or were walking towards the participant. On the day participant P6 visited, some corridors were encumbered by one or more ladders due to ongoing work. In this case, we directed the participant by voice to avoid the ladder.

3.3 Participants and Procedure

Eight blind volunteers and five sighted volunteers participated in the study. The blind participants were recruited through the network of acquaintances of the second author, while the sighted participants were graduate students or faculty members in our school. Note that the focus of this data set is on blind walkers; we added data from sighted participants only as a "control," for comparison in identical settings.

3.3.1 Blind Participants

Participant P1 is a 66-year-old woman who has been blind since she was very young. She has a guide dog, a Labrador Retriever, who is functioning, but close to retirement. P1 feels that her dog is becoming distracted and is not as good as he used to be at staying away from obstacles, and for this reason she recently took some classes to refresh her long cane skills. She walked paths T1 to T4 with the dog first, then again with the cane. She then walked paths T5 and T6, with the dog first, and then again with the cane. She felt that using the dog allowed her to walk on a straight line, while she tended to veer while walking with the cane; this was confirmed by our observations. Her dog, which she held on a harness with her left hand tended to keep very close to the right side of the wall. When walking with the cane, P1 sometimes got stuck in a wall opening and had to walk away from it to resume her path. She slides her pencil-tipped cane left and right, synchronized with her gait.

Participant P2 (aged 46) lost her sight over the past five years due to diabetic retinopathy (the diabetes also caused some neuropathy at her feet). She uses a long cane for mobility, although she is looking forward to receiving a guide dog in the near future. She is still perfecting her mobility skills, and feels that she is not moving as gracefully as other people in her condition. Her cane has a ball tip; she slides it left and right, synchronized with her gait. She often hit a sidewall with her cane, and sometimes bumped into obstacles along the way (e.g., a garbage bin or a chair).

At 26 years of age, P3 was the youngest participant in our study and she has been blind since birth. An expert cane user, she had a guide dog in the past. She, however, admits that her orientation skills are poor, so she was glad to hear that this study required no route memorization. P3 was able to walk on straight paths without much veering; however, she did get caught in a wall opening a few times. She uses a cane with a ball tip, sliding it on the floor in a swinging motion that, however, is generally not synchronized with her gait.

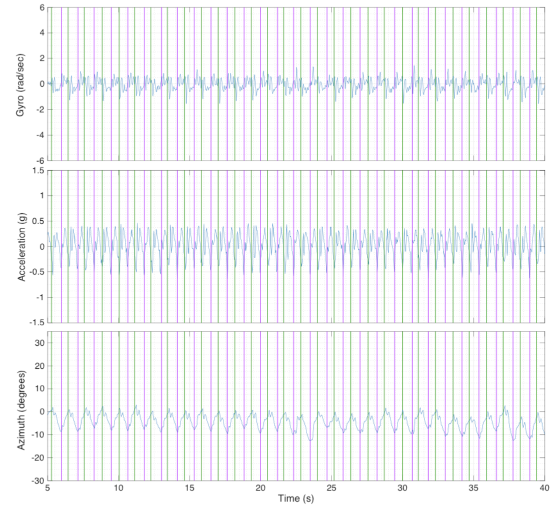
Participant P4 is a 65-year-old woman who lost her sight soon after birth. She didn’t bring her cane, and thus was tested only with her dog, an energetic German Shepherd, who walked very fast as she held the harness with her left hand. The dog followed P4’s commands faithfully, although at one point, while in the stairwell that joins two corridors, he almost started leading P4 downstairs instead of walking straight past the staircase. P4 explained that the dog might have been wanting to walk to P4’s husband, who was waiting downstairs in the parking lot.

Participant P5, aged 59, is a man who lost his sight at 18 months of age. He never had a guide dog, and is not interested in one. He is an expert traveler, with excellent orientation skills. He often travels independently by public transit. He had a peculiar way of using his pencil-tipped cane. Instead of swinging his cane left and right, he holds it at an angle in front of him, and taps it on the ground at regular intervals. He explained that, by listening to the sound and its echo, he could tell the presence of nearby surfaces. He walked, for the most part, with very little veering.

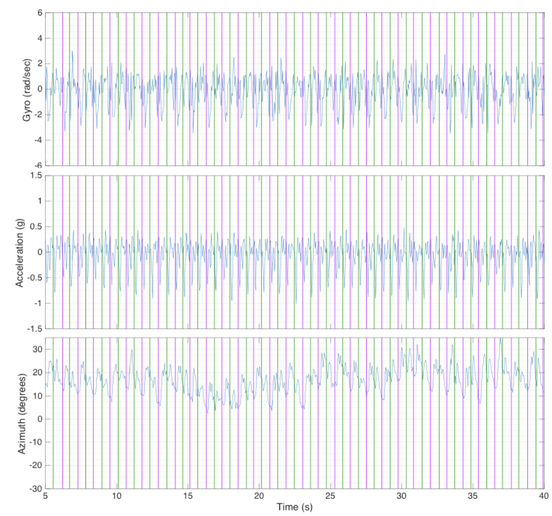
Participant P6 is a 68-year-old man. He lost his sight due to a traumatic brain injury as a teenager. P6 used a telescopic cane with a round metallic glide tip, which he maneuvers in a swinging motion synchronized with his gait. He slid the cane on the floor except for the outside terrace with rugged concrete surface, where he instead tapped it (2-point touch). P6 explained to us that he normally uses a different, heavier cane when walking outdoors. He was able to walk in straight lines and avoided almost all obstacles, without hitting any wall or being caught in wall openings.

Participant P7 is a man, aged 46, who has been blind since birth. He has excellent orientation skills and regularly travels even long distances using public transportation. He uses a single piece long cane with round metallic glide tip, which he slides on the floor in a swinging movement synchronized with his gait. In our trials, he walked with little veering. In a couple of occasions, he bumped his shoulder into large obstacles along the path.

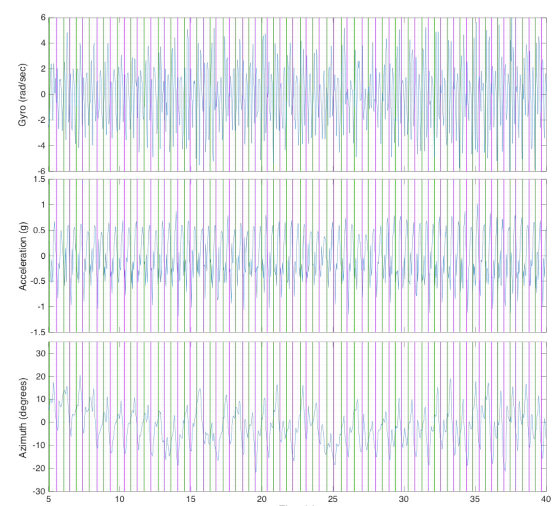
Participant P8 is a 69-year-old woman who lost her sight progressively during her young age. Similar to P1, she walked all paths twice, one time with her guide dog and the other time using a long cane (pencil tip). She is a proficient traveler, yet she often times veered off the straight direction when walking in a corridor and had to correct her path.



(a) A sighted participant



(b) Participant P3 using a long cane



(c) Participant P6 using a guide dog

Figure 4. Time series of measurements from accelerometer, gyro, and azimuth. The magenta and green vertical lines mark the left and right foot strikes.

3.3.2 Smartphone Placements

Each participant was asked to choose a comfortable location for the two smartphones used in order to take inertial measurements during the trials. Preferences varied: sometimes a smartphone was placed in the front or back pants pocket, while in other cases it was placed in a holster clipped to the participant's belt, in a jacket pocket at waist or breast height, or tucked under the participant's shirt at shoulder level. Tab. 1 shows the different placements for our blind participants. Informal surveys (e.g. [19]) have shown that the majority of people keep their phone in their pocket, and for this reason we didn't consider placement of the smartphones in the participants' handbag or backpack. In addition, step counting with smartphone in a handbag was shown to be inaccurate [5] due to extra swinging of the bag. We also didn't consider the case of a smartphone held in one's hand while walking, as this may be inconvenient for blind people who already have one hand occupied holding a cane or a guide dog.

3.3.3 Procedure

After signing the IRB-approved consent form, each participant was shown the CPRO sensors in their clip cases, and asked to clip each sensor case to the back, if possible, or to the side of their shoe (see Fig. 2). (Note that participants were advised in advance of their visit to wear comfortable shoes, and to wear clothing with pockets.) Then, the participant was asked to position the two smartphones, as discussed in Sec. 3.3.2. Participants were advised not to pay attention to any speech produced by the smartphones (which were programmed to utter short synthetic speech verification sentences upon successful pairing with the control phone). Participants were also advised to begin walking when prompted by an experimenter, and to walk straight until asked by the experimenter to turn left or right (or, in the case of path T5, to turn around), to push or pull open a door, or to stop at the end of the path. These were the only verbal directions provided to the participants, except for occasional safety warnings (e.g., as mentioned earlier, participants were advised to walk closer to one side of a corridor if there were obstacles on the other side).

Figure 5. Four of our blind participants dealing with specific situations. Top two images: being caught in wall opening. Bottom left: pushing open a door. Bottom right: avoiding an obstacle (a ladder) in the way.

No training on the use of the system was necessary, since the task was for the participants to simply walk naturally. Each participant first went through the pre-trial described in Sec. 3.1.2 for ground truth calibration. Then, he or she was accompanied to the start position of the first path, and asked to start walking in the designated direction. Before the start of each path, participants were oriented to face the correct direction; this was particularly important for paths T2, T5 and T6, which started with diagonal traversal of an entrance or elevator hall. All trials with blind participants were supervised by two experimenters. One of the experimenters managed the start and end of data collection from all sensor platforms via the control phone, and recorded videos of all sessions by means of a GoPro HERO Session camera attached to a head strap. The other experimenter walked at a close distance behind or sometimes in front of the participant, and was in charge of ensuring the participant's safety.

Fig. 4 shows an example of time series collected during a straight path in route T3 for three individuals: a sighted participant, a blind participant using the long cane, and a blind participant using a guide dog. For the accelerometer and the gyroscope sensors, the first and second subfigures plot a linear combination of the time series from the three axes, corresponding to the principal component. The azimuth data (angle around the vertical) was obtained from the iOS CoreMotion Framework, and is defined with respect to an arbitrary horizontal axis. (Note that the magnetometer is not used for this purpose, as we found that it decreases the quality of the azimuth in indoor environments.) The plots also display the heel strikes times (shown by vertical lines) for each foot. Observation of the azimuth time series provides some insight into the gait characteristics of each individual. In particular, the sighted walker maintained a steady heading direction (with oscillation due to natural body swinging). The azimuth time series of the blind walker with a cane shows a more variable pattern, with variation in heading direction as large as 20 degrees. The blind participant using a guide dog maintained a more stable heading direction, but with a wider swinging action.

3.4 Data Annotation

After completion of all trials for a participant, the data from all sensors was offloaded to a desktop computer for post-processing. In particular, all data streams were synchronized as discussed in Sec. 3.1.1. The video streams collected from the GoPro camera were also synchronized to the same time base used for the sensors. The heel strikes times for each foot (computed by the CPRO sensors, Sec. 3.1.1) was recorded.

The time lapse during traversal of a route was divided (by visual inspection of the video) into contiguous intervals, where each interval corresponds to either a straight segment in the path, or to a "turn" event. For example, traversal of route T1 (shown in Fig.1) was divided into seven contiguous time intervals, corresponding to four straight patches interleaved with three 90 degrees turns. The cardinal direction of each straight path, or of the paths joined by a turn, was recorded in the annotation file, together with the start and end time of each interval, and with the number of steps taken during the interval. In addition to the segmentation into straight paths and turns, we created annotations of particular events such as opening a door, bumping into an obstacle, being caught in a door opening, or stopping momentarily (see Fig. 5). These events are normally associated with anomalous characteristics in otherwise regular inertial data time series (see Figs. 6–8). Also note from these figures that when participants are engaged in tasks such as opening a door, the shoe-mounted

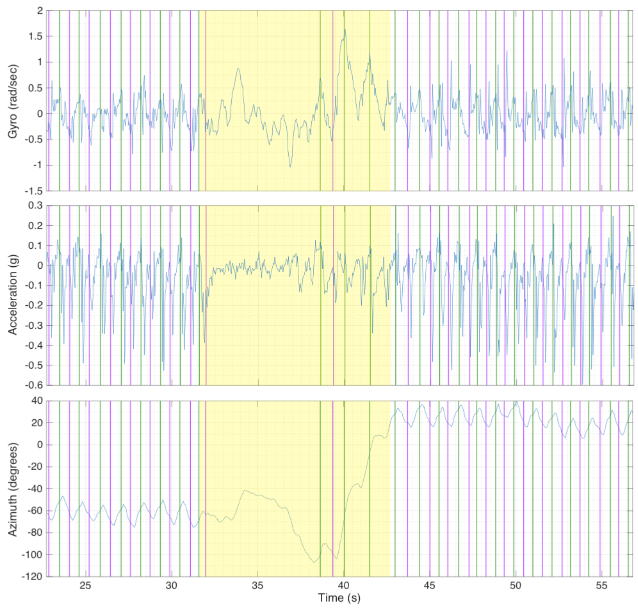


Figure 6. Sensor data from a participant pulling a door open then making a left turn.

sensors sometimes detected "phantom steps" when in fact the participants were simply balancing themselves on their feet. We did not manually remove these phantom steps, as they occurred only sporadically in our study. All of the data was annotated by one experimenter and independently checked and verified by another experimenter. The annotation file, which is stored using the Extensible Markup Language (XML) format, also includes other relevant information such as the type of mobility tool used, as well as some general gait pattern observations.

4. DERIVED DATA EXAMPLES

In this section we show some simple examples of the different types of analysis that can be carried out on the inertial data in WeAllWalk. These examples are not meant to test specific hypotheses, but simply to highlight the richness of the data in our data set, and to suggest directions for future research.

4.1 Step Counting

After experimenting with several of the algorithms mentioned in Sec. 2.2, we found that the best step detection results for our data were produced by the AMPD technique of Scholkmann et al [34]. This algorithm processes the magnitude of the acceleration, and finds the peaks associated with heel strikes by detecting local maxima. We used a Savitzky-Golay filter [33] to smooth the accelerometer magnitude before computing local maxima. We then compared the step detections (computed on the data from the iPhones) with the ground truth data from the foot-mounted sensors. Rather than simply counting the total number of steps in a certain path, we used a more conservative metric, defined as following. Given the interval T between two consecutive ground truth heel strike times, and the number n of steps detected within this interval, we declare an *undercount event* if $n = 0$ (no steps detected within interval T) and number n - 1 of *overcount events* if $n > 1$ (more than one step detected within T). We then report errors in terms of rates of undercount and overcount events. Fig. 9 shows step counting errors computed over the whole set of trajectories for sighted participants, blind participants using a cane, and blind participants using a guide dog. Note that the same

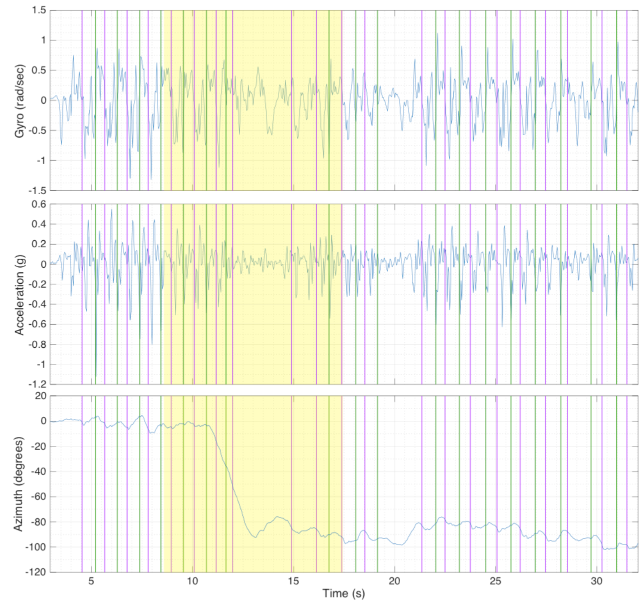


Figure 7. Sensor data from a participant making a right turn then pushing a door open.

algorithm (with the same parameters) was used for all participants. This data seems to suggest that larger errors are obtained with this algorithm for blind walkers; a thorough statistical analysis to evaluate this hypothesis is planned as future work.

4.2 Turn Detection

An indoor route can often be expressed in terms of a sequence of turns, along with the number of steps taken in the path between two consecutive turns. For example, one may specify a route as: "Walk straight through this corridor for about 50 steps, then make a left at the junction, walk for 20 more steps and take a right at the first corridor." Note that for most buildings, corridors intersect at angles of 90 or, in some cases, 45 degrees. Robust detection of turns from inertial data from a smartphone, combined with step

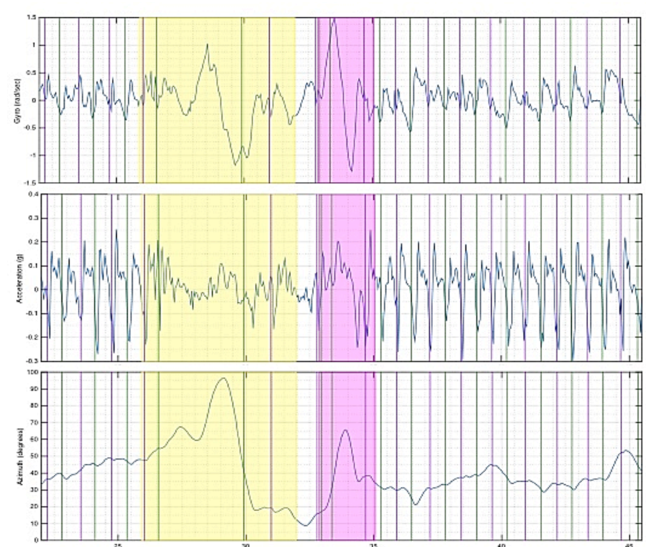


Figure 8. Sensor data from a participant being caught in a door opening (yellow area) then hitting her arm against the wall (magenta area).

counts between turns, may help blind travelers keep track of their progress in an indoor route. If a walker at some point feels lost, he or she may be able to return to the starting point (e.g., an entrance door) by simply following the sequence of recorded turns in reverse order.

Turn detection can be achieved by analyzing azimuth data, which represents the walker's heading direction. However, care must be taken in the case of wide swinging or veering during walking, which may trigger false turn detection. In addition, drift in the measured azimuth may accumulate during a long path, which may complicate the job of algorithms that detect turns by simply thresholding the heading direction.

An algorithm for robust turn detection based on a hidden Markov model (HMM) was introduced by Flores et al [11]. This algorithm was shown to be resilient to drift. It can be designed to detect turns of 45 or of 90 degrees; in the case of 45 degrees turn detection, consecutive detected turns within a short time interval are "clustered" together to form a 90 degree turn.

We show results of turn detection based on azimuth data using this algorithm in Figs. 10 and 11 for two different routes (T4 and T5) and for two different individuals: a sighted participant, and a blind participant using a long cane. The system was set to detect turns of 90 degrees in the first case, and turns of multiples of 45 degrees in the second case (note that T5 begins with a 45 degree turns). As noted earlier, the heading direction for the blind participants tend to be less steady than for sighted walkers, which may complicate the job of the turn detector and, as in the case of these examples, result in occasional false positives.

5. CONCLUSIONS

We have introduced a new data set with inertial sensor time series collected from blind walkers. Our participants walked through fairly long and complex routes; on their way, they sometimes had

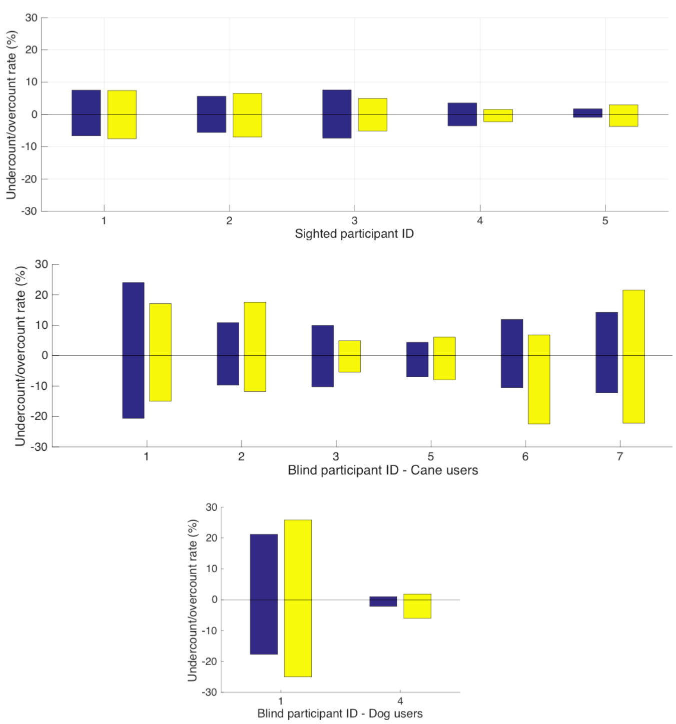


Figure 9. Step over count rate (positive bars) and undercount rate (negative bars) for sighted participants, blind participants using a long cane, and blind participants using a guide dog.

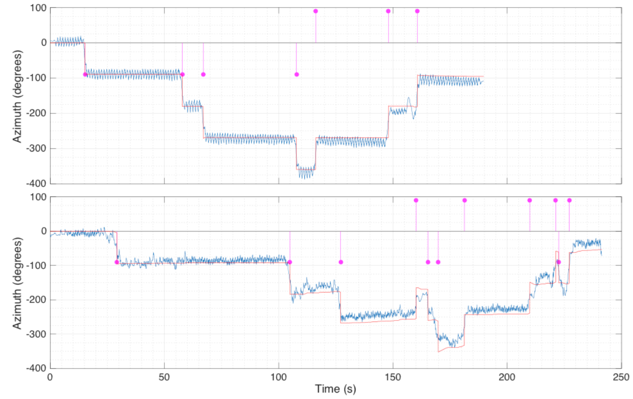


Figure 10. Azimuth time series for a sighted (top) and a blind participant (bottom) walking on Path T4. Pink stems: turn angles (left or right) that are multiple of 90 degrees. Red line: estimated heading direction.

to open doors and avoid obstacles. The data has been subdivided into straight paths and turns, and carefully annotated, with special events (such as bumping into an obstacle) individually identified and marked. Simple examples of applications such as step counting and turn detection have been presented, which highlight some of the peculiar characteristics of blind ambulation as measured by these sensors.

While we believe that this data can be useful to several researchers who are interested in personal mobility, we are also aware of some of its shortcomings. For example, although our participants were asked to walk naturally, they didn't have to find their way independently (as they were instructed when to turn). Participants may also have felt self-aware, as they were being followed and observed, and thus may not have been fully natural (for example, they may have put extra effort to avoid obstacles). All of our routes were indoors, and thus our data is not representative of outdoor ambulation. As one of our participants explained, some blind travelers pay attention to different things when walking indoors and outdoors. For example, when walking indoors, they may be careful of avoiding obstacles such as a door left ajar; while in the outdoors, typical concerns include the condition of the pavement, and the possibility of a hole or a curb.

6. ACKNOWLEDGMENTS

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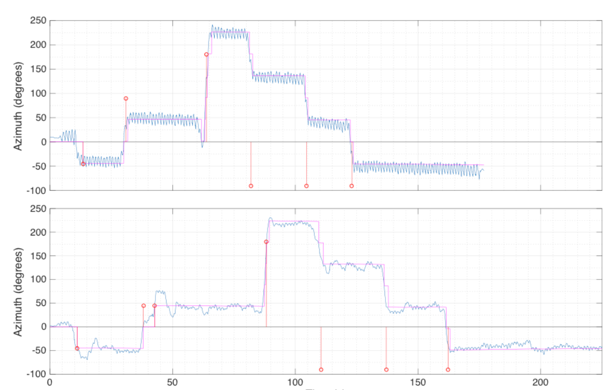

Figure 11. Azimuth time series for a sighted (top) and a blind participant (bottom) walking on Path T5. Red stems: turn angles (left or right) that are multiple of 45 degrees. Pink line: estimated heading direction.

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