



The 11th International Conference on Mobile Systems and Pervasive Computing (MobiSPC-2014)

## Early Diagnosis of Parkinson's Disease using a Smartphone

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### Abstract

Diagnosing Parkinson's disease (PD) is often difficult, especially in its early stages. It has been estimated that nearly 40% of people with the disease may not be diagnosed. Traditionally, the diagnosis of Parkinson's disease often requires a doctor to observe the patient over time to recognize signs of rigidity. In this work, we propose a PDR-based method to continuously monitor and record the patient's gait characteristics using a smart-phone. Our tool could be useful in providing an early warning to the PD patient to seek medical assistance and help the doctor diagnose the disease earlier.

*Keywords:* pedestrian dead reckoning, parkinson's disease, gait characteristics, smartphone

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### 1. Introduction

Gait disturbance is an early feature of brain disorder such as Parkinson's disease, dementia and stroke which lead to apraxic gait patterns where there is loss of ability to move properly. This is due to the disruption of the human locomotion control and sensory feedback system, which controls balance allowing safe negotiation of the environment. Several prior studies have showed how a person walks may predict whether they'll develop Alzheimer's or Parkinson's disease. Mobility impairments are often associated with these brain disorders, and some gait changes may even appear before cognitive decline can be detected by some selected gait characteristics such as gait speed and stride length. For example, [1] found that found slower walkers with a lower cadence and less of a stride length were more likely to have problems in cognitive, memory and other processing functions, compared to

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faster walking counterparts. These studies suggest that continuous monitoring of changes of gait characteristics may provide useful information at detecting motor changes associated with future cognitive decline.

In this work, we propose a method that utilizes the accelerometer sensor in a smart-phone to continuously monitor the changes of walking patterns of a potential patient who might be developing some brain disorder like Parkinson's disease. Tracking people is an important component of ubiquitous networking. In this paper, we consider the use of a pedestrian dead reckoning (PDR) system to capture the gait characteristics, such as step length and step frequency, of a person. On average, the accuracy of our step length estimation is about 98%. Using a simple binary classification method like SVM, we also show that we can identify the changes of walking pattern of the patient using the recorded gait data from the phone with high accuracy.

## 2. Related work

A PDR system can be classified into two types depending on where the sensor is mounted: foot-mounted [6] and waist-mounted [8-10]. To calculate the step length, the foot-mounted methods typically perform a double integral on the horizontal acceleration. However, without further calibration, the problem of sensor drift [7] could introduce serious inaccuracies when estimating the step length. One way to calibrate the sensor drift error is called zero velocity update (ZUPT). When the swinging-foot touches the ground, the angular velocity of this foot will be close to zero, which can be used to reset the system to avoid sensor drift errors accumulating into the length estimation of the next step.

On the other hand, for a waist-mounted PDR system, ZUPT is not directly applicable, since one will not be able to find zero velocity in the horizontal direction. Some waist-mounted PDR systems use a constant step length [2-5] while the others [9] use a trace-driven approach, by first collecting empirical data from multiple users and then using linear regression to find the relation between step length, walking frequency, and the variance of acceleration. The limitation of this approach is that one might need to collect new training data for a new user. Weinberg [10] observed that the upper body moves vertically when walking, and suggested that one can estimate the step length as follows:  $StepLength = 2 \times heightchange / \alpha$ , where  $\alpha$  is the swinging angle of the leg from the body, and the *heightchange* can be estimated based on the vertical acceleration. However, he did not discuss how to measure  $\alpha$ . Our idea is similar to Weinberg's, but we estimate the step length based on the height change and length of the leg using the Pythagorean Theorem. In addition, we use the concept of Simple Harmonic Motion (SHM) to find the zero velocity in the vertical direction, and apply ZUPT to avoid the accumulation of sensor drift errors on the vertical-axis.

## 3. Sensing gait characteristics using a smart-phone

As described above, Weinberg [10] proposed that one can estimate the step length using the height change of the waist and the swinging angle of the leg during walking, but he did not discuss how to measure this angle, and we found that, in practice, it is difficult to measure such a small angle during walking. Based on Pythagorean Theorem, in this paper we proposed a different way to estimate step length using the change in height. During walking, a person's body moves up and down. If we assume the length of the leg is  $L$ , the waist-line will move up-and-down between  $L$  and  $(L-h)$  from the ground, where  $h$  is the change in the height of the waist. Considering the triangle in Figure 1, formed by two feet of a person and their step length  $D$ . Given that  $L$  is known, using the Pythagorean Theorem, we can estimate  $D$  if we know the height of this triangle, i.e.,  $(L-h)$ . To obtain  $(L-h)$ , we first need to calculate  $h$ , which is the change in height of the waist during walking. Therefore, if we mount an accelerometer on the user's waist, the readings of this can be used to estimate the height change  $h$ , which can then be used to calculate the step length  $D$  based on the Pythagorean Theorem (the length of the leg (i.e.  $L$ ) and half of the step length (i.e.

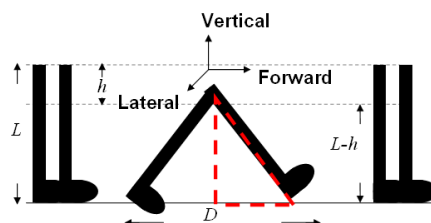


Figure 1: Walking Diagram

$D/2$ ) forms a right triangle in which leg length is the hypotenuse).

In this paper, we extend the above-mentioned waist-mounted method for a smart-phone. When implementing a PDR system on a smart-phone, two cases can be considered. The first is when the user holds the phone (e.g., when talking on the phone), and the other is when the phone is put in a pocket or a bag. Prior research [14] has shown the feasibility of using a waist-mounted method for the first case. Therefore, in this paper we focus on how to extend the results of a waist-mounted method for the second case. To implement a waist-mounted method, two issues need to be considered: the orientation and placement of the phone. The orientation of the phone may change from time to time when it is put in a pocket or bag during walking, and this affects the influence of gravity on the three axes of the accelerometer, and results in different readings from the sensor. To resolve this problem, we adopt a method similar to that in an earlier work, Su et al. [14], which used a gyroscope to record changes in orientation and to calibrate the system. Next, in a waist-mounted method, the vertical movement displacement of the phone is the key parameter to estimate the step length. When the phone is positioned above the waist-line, its vertical displacement during walking will be the same as when it is mounted on the waist. On the other hand, when the phone is placed below the waist-line (e.g., in a pants pocket), we can estimate the vertical displacement of the waist as follows. Assuming the leg length ( $L$ ) and the pocket position from the ground ( $L'$ ) are already known, we can find two similar triangles  $\Delta ABC$  and  $\Delta PQR$ , as shown in Figure 2. Based on the Pythagorean Theorem, we can obtain  $h'$  by first measuring  $L'$  and  $h'$  (i.e., the vertical displacement of the pocket during the walking). Then, using triangle similarity, we can find  $D$ .  $h'$  can be measured in a similar way as to measure  $h$ .

To use the smart-phone to estimate the walking distance, the following practical issues need to be considered:

1. How to remove signal noise, such as vibrations from the body?
2. How to prevent sensor drift errors accumulating from one step to the next?
3. How to deal with when the user moves at irregular speeds?

Our system architecture is shown in Figure 3. We first filter the noise using a low-pass filter. The filtered signal is fed into the step recognition module to identify each new step. We adopt the concept of simple harmonic motion

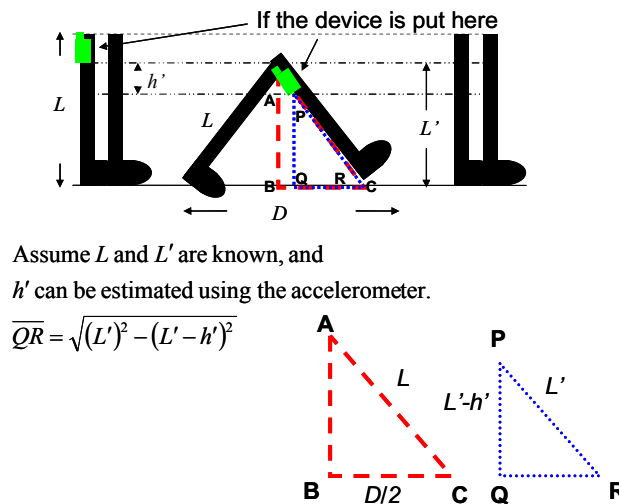


Figure 2: When the device is mounted on the lower body

(SHM) [11] to reset the vertical velocity at the beginning of each new step, which prevents sensor drift errors from being accumulated over to the next one. Finally, the step length is estimated based on the filtered sensor data and foot length.

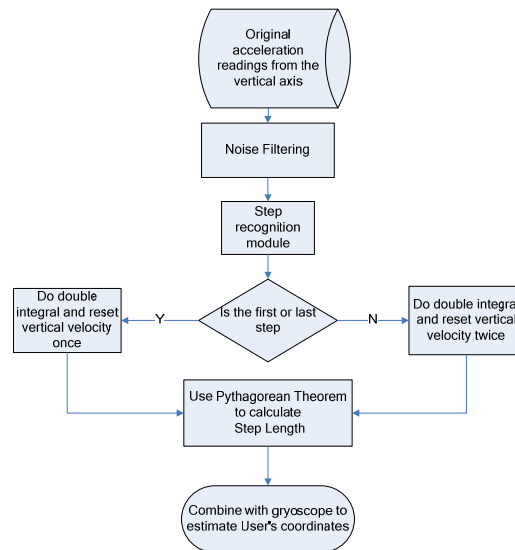


Figure 3: Flow chart of our step length estimation algorithm

### 3.1. Noise Filtering

During walking, some unexpected and unpredictable body vibrations might cause some higher-frequency noise in the sensor readings. In this section, we discuss how to filter such noise.

Intuitively, one can use a low pass filter and preset a cut-off frequency to filter noise. Some prior work has shown that the frequency of human muscle movement is lower than 16Hz [12], and the human step frequency is never higher than 3Hz [8]. Therefore, some step recognition systems use 3Hz as their cut-off frequency to filter noise signal [4]. Initially, we also used 3Hz, but then found our results became worse. This shows that, while it is good enough to detect a new step event, a 3Hz threshold is too low for our purposes, and will remove data which is not noise. Some prior research [13] analyzed the acceleration of the waist during walking, and found the maximum acceleration is 8Hz. We thus set our cut-off frequency at 8Hz for filtering the noise, and this threshold worked well under repeated experiments with different subjects.

### 3.2. Step recognition module

In order to recognize a step, we first analyze the components of one step that can cause vertical changes to the body. There are three major events which may affect the height of the waist, as shown in Figure 4.1. The first one is a heel-touching-ground event, which happens when the heel just hits the ground and the waist is in its lowest position during the entire step. The event that comes after this is the stance, which occurs when the foot is flat on the ground. Finally, the heel-off-ground event occurs right after the stance. Generally, as shown in Figure 4.2, the vertical acceleration of a heel-touching-ground event is the local minimum within a step. In addition, previous studies [2] showed that human walking frequency is never over 3Hz. Therefore, the duration between two consecutive heel-touching-ground events must be over 0.33 second. Based on the above, we use a sliding window algorithm to detect every heel-touching-ground event, and define one step as from a heel-touching-ground event to the next heel-touching-ground event. Once a new step is identified, the sensor data between two consecutive heel-touching-ground events will be used to estimate the step length.

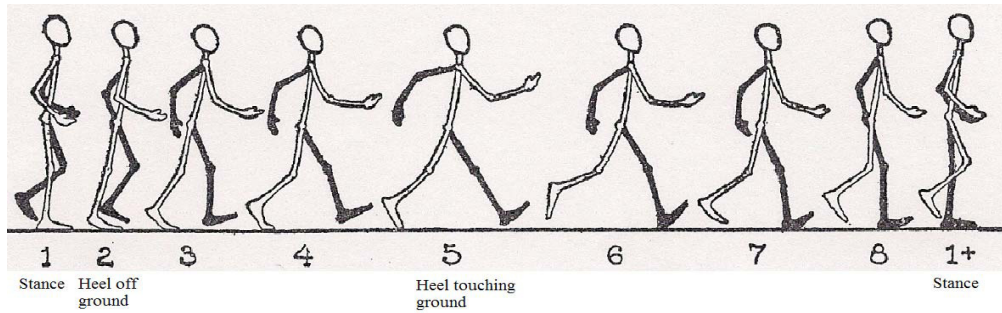


Figure 4.1 Walking diagram (modified from [16])

### 3.3. Step length estimator

#### 1) Our step model

To measure the walking distance from point A to point B, we sum up the step length of all steps. We model a complete step as from one heel-touching-ground-event to the next. Therefore, we consider the first step (i.e., from the stance event to the heel-touching-ground event, as shown in Figure 4.1) and the last step (i.e., from the heel-touching-ground event to the stance event) as half a step. When the first or last step is detected, our system will divide the calculated step length by 2.

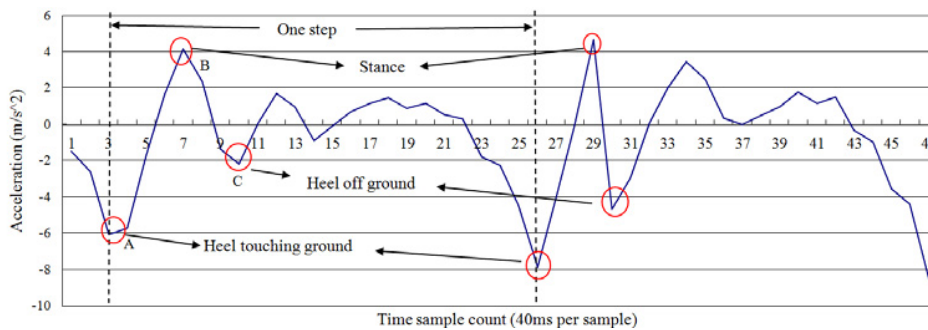


Figure 4.2: The vertical acceleration of walking

#### 2) Avoid accumulation of sensor drift errors

Once each step can be identified, we can then do the double integral to calculate the height change of the waist and then use this information to estimate the length of each stride based on the Pythagorean Theorem. However, as discussed previously, if the system only naively does the double integral on the accelerometer data, the sensor drifts errors could accumulate from one step to the next. To avoid this, we propose a zero velocity update method to calibrate the sensor data: if we mount a sensor on the waist of a pedestrian, then while they are walking the trajectory of the sensor can be approximated by Simple Harmonic Motion (SHM) [11]. In addition, given that the velocity of the highest and lowest points of the sensor will be zero, we can utilize these characteristics to detect when the user starts a new step. Finally, once the points with zero velocity in the vertical direction (where the vertical acceleration reaches its local maximum, i.e., points A and B in Figure 4.2) are identified, we can then reset the vertical velocity to

zero before doing the double integral for calculating the height change of the user’s waist. The height change can then be used to estimate the step distance based on the Pythagorean Theorem.

Specifically, there are three major events during one step, namely heel-touching-ground, stance, and heel-off-ground. As shown in Figure 4.2, the lowest valley (point A) of the wave indicates when the heel is touching the ground (corresponding to the fifth posture in Figure 4.1), the first peak occurs (point B) when the walker is in the stance state (corresponding to the first posture in Figure 4.1). Following the stance event, the body starts to lean forward and the foot is now on its toes, which will give a force to push the body up, so that the vertical acceleration will change to the opposite direction and cause the second valley in Figure 4.2 (i.e., point C, corresponding to the second posture in Figure 4.1), due to the law of inertia.

As shown in Figure 4.1, when the stance and heel-touching-ground events occur, the waist has the largest displacement from its equilibrium position. Therefore, we reset the vertical velocity to zero at these points. We performed an experiment to observe the effect of doing such a zero velocity update (ZUPT). As shown in Figure 5, implementing ZUPT can indeed avoid the accumulation of sensor drift errors.

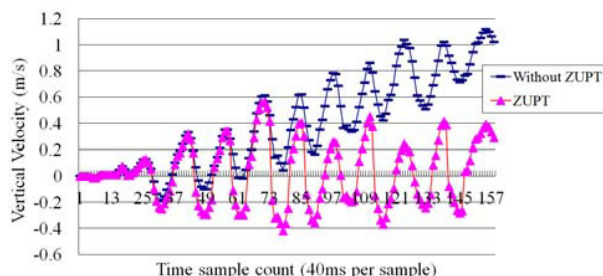


Figure 5: the velocity with ZUPT versus without ZUPT

The first and last steps are considered as special cases. There is only one point where the velocity needs to be reset, because the initial velocity of the first step is already zero, and the last step does not need to reset this when the body is in its stance state.

3) Moving at high speed or on the same spot

As shown in Figure 4.2, when one walks at a normal speed, the stance event generally occurs as the first peak after the heel-touching-event. However, during high speed movement, we observe that the counter-force from the ground could introduce an extra pulse between the heel-touching-ground and stance events. Without taking this into consideration, our system could reset the velocity at the wrong point. Previous studies in kinesiology [15] showed that the duration from the heel-touching-ground event to the stance event normally accounts for at least 16.7% of the time in a step. Based on this observation, we can identify the right point where the stance event occurs and reset the velocity when calculating the step length.

When one is moving on the same spot, the acceleration data should not be considered in the calculation of step length. In addition, when one is walking on the same spot, the height of the waist does not usually change significantly. Therefore, we use a simple threshold-based filter to detect this phenomenon by looking at whether the acceleration data in all three directions (vertical, horizontal, and lateral) are lower than a certain threshold,  $\epsilon$ , as shown below, and then reset the vertical acceleration accordingly (in our implementation,  $\epsilon$  is set to 1m/s<sup>2</sup>).

$$verticalAcc = 0, \tag{1}$$

$$if \ |lateralAcc| < \epsilon \ \& \ |horizontalAcc| < \epsilon \ \& \ |verticalAcc| < \epsilon$$

#### 4. Evaluation

We implemented our PDR-based step length estimation algorithm on a variety of Android phones from HTC and Samsung. The phones were given to 17 seniors in a senior center used as a step counters to record their daily activity level since May 2012. The collected data are also periodically uploaded to a server.

As discussed previously, we use a low-pass filter to filter out the noise in our step length estimation algorithm. We choose 8Hz as our cut-off frequency for filtering the noise because it gives us the most accurate results. Some of the state-of-the-art pedometers on the market can also output walking distance. We compare our method with these pedometers, and find that they only achieve up to 90% accuracy, which is significantly lower than our results (98%).

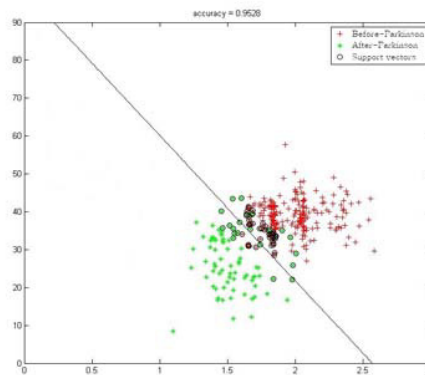


Figure 6: Detection of changes of gait characteristics via SVM (x-axis: step frequency ; y-axis: step length)

Furthermore, as discussed previously, our approach is based on the idea of using the change in height of the waist to estimate step length, which is similar to the method used in Weinberg [28]. In his work, he proposed an equation to estimate distance by observing the vertical acceleration during walking. We implement Weinberg’s method and find that its accuracy is about 96.7%. In addition, one limitation of Weinberg’s approach is that its system parameters need to be re-trained for every new user. In our system, we use a low-pass filter (LPF) to filter out the noise and employ zero velocity update (ZUPT) to calibrate the drift error of the accelerometer. To understand the effects of these mechanisms, we enable only one of them at a time. As shown in TABLE 1, ZUPT has a higher impact on the system performance than the implementation of the low-pass filter. When ZUPT is disabled, the accuracy drops

TABLE 1. COMPARISON WITH OTHER WAIST MOUNTED METHODS AND THE INFLUENCE OF THE MECHANISM

Method	Pedometer	Weinberg	Ours (A: LPF, B: ZUPT)			
	Constant step length × step number	$k \times n \times \sqrt[4]{Acc_{max} - Acc_{min}}$	Original (A+B)	A	B	None
Accuracy (Estimation/ Ground truth)	90.09%	96.78%	98.25%	84.1%	95.29%	75.53%
Standard deviation	1.83%	3.18%	1.29%	7.41%	2.22%	16.3%

from 98.25% to 84.1%.

The feasibility of our proposed approach to detect Parkinson's disease's development was demonstrated by a recent event. One of the seniors who used our phone was diagnosed with Parkinson's disease in early this year. We find his step length (cm) and step frequency (number of steps/second) decreasing over time, as shown in Figure 6, through the examination of collected smartphone data. With a binary classification method like SVM, we can easily identify such a change of his walking patterns and provide an early diagnosis of his Parkinson's disease.

## Conclusion

Diagnosing Parkinson's disease is often difficult, especially in its early stages. It has been estimated that nearly 40% of people with the disease may not be diagnosed. Traditionally, the diagnosis of Parkinson's disease often requires a doctor to observe the patient over time to recognize signs of rigidity. In this work, we propose a PDR-based method to continuously monitor and record the patient's gait characteristics using a smart-phone. Our tool could be useful in providing an early warning to the PD patient to seek medical assistance and help the doctor diagnose the disease earlier.

## References

- [1] Stephanie A. Bridenbaugh and Reto W. Kressig, "Quantitative Gait Disturbances in Older Adults with Cognitive Impairments", *Current Pharmaceutical Design*, Des. 2013
- [2] C.-C. Shih. "The Implementation of a G-Sensor-based Pedometer," M.S. paper, Dept. C.S.I.E., National Central Univ., Taoyuan County, Taiwan 2010.
- [3] F. Jorgensen, "Accurate step counter," U.S. Patent 0 172 203 A1, Jul. 17, 2008.
- [4] M. Martin, and M. Michael, "A step counter service for Java-enabled devices using a built-in accelerometer," presented at Proceedings of the 1st International Workshop on Context-Aware Middleware and Services: affiliated with the 4th International Conference on Communication System Software and Middleware (COMSWARE 2009), Dublin, Ireland, 2009.
- [5] P.L. Schneider, S.E. Crouter, O. Lukajic, and D.R. Bassett, "Accuracy and reliability of ten pedometers for measuring steps over a 400-m walk.," *Medicine & Science in Sports & Exercise*, vol. 35, 2003, pp. 1779-1784.
- [6] L. Ojeda, and J. Borenstein, "Personal Dead-reckoning System for GPS-denied Environments," in 2007 IEEE International Workshop on Safety, Security and Rescue Robotics (SSRR 2007), 2007, pp 1-6.
- [7] D.H. Titterton, and J.L. Weston, "Strapdown Inertial Navigation Technology," Peter Peregrinus Ltd, 1997.
- [8] F. Lei, P.J. Antsaklis, L.A. Montestruque, M.B. McMickell, M. Lemmon, S. Yashan, F. Hui, I. Koutroulis, M. Haenggi, X. Min, and X. Xiaojuan, "Design of a wireless assisted pedestrian dead reckoning system - the NavMote experience," *IEEE Transactions on Instrumentation and Measurement*, vol. 54, 2005, pp. 2342-2358.
- [9] S.H. Shin, C.G. Park, H.S. Hong, and J.M. Lee, "MEMS-Based Personal Navigator Equipped on the User's Body," presented at ION GNSS 18th International Technical Meeting of the Satellite Division, Long Beach, CA, 13-16 september 2005.
- [10] H. Weinberg, "Using the ADXL202 in Pedometer and Personal Navigation Applications," in *Application Notes American Devices*, 2002.
- [11] Simple Harmonic Motion, Available: [http://en.wikipedia.org/wiki/Simple\\_harmonic\\_motion](http://en.wikipedia.org/wiki/Simple_harmonic_motion)
- [12] B. Gerald and T. Andreas, "DiaTrace - Neuartiges Assistenz- System für die Gesundheitsprävention zur Nahrungsaufnahme und Bewegungserfassung," in *Deutscher Kongress mit Ausstellung / Technologien - Anwendungen – Management*, Berlin, Germany, 2008.
- [13] Chen, K.Y and Bassett, D.R., "The technology of accelerometry – based activity: monitors: current & future", *American College of Sports Medicine*, 2005.
- [14] C.-M. Su, J.-W. Chou, C.-W. Yi, Y.-C. Tseng, and C.-H. Tsai, "Sensor-aided personal navigation systems for handheld devices," in *Proceedings of the 2010 39th International Conference on Parallel Processing Workshops*, ser. ICCPPW '10. Washington, DC, USA: IEEE Computer Society, 2010, pp. 533–541.
- [15] K. Chintalapudi, A. P. Iyer, and V. N. Padmanabhan, "Indoor Localization Without the Pain," in *16th ACM International Conference on Mobile Computing and Networking (MobiCom 2010)*, Chicago, IL, September 2010, pp. 173–184.
- [16] Walking diagram, available: <http://www.juliecallahan.me/walkcycle.jpg>