GaitTrack: Health Monitoring of Body Motion from Spatio-Temporal Parameters of Simple Smart Phones

Qian Cheng, MS
Department of Computer Science
University of Illinois at Urbana-Champaign
Urbana, Illinois, 61801
qcheng4@illinois.edu

Joshua Juen, MS
Department of Electrical and Computer Engineering
University of Illinois at Urbana-Champaign
Urbana, Illinois, 61801
juen1@illinois.edu

Yanen Li, MS
Department of Computer Science
University of Illinois at Urbana-Champaign
Urbana, Illinois, 61801
yanenli2@illinois.edu

Valentin Prieto-Centurion, MD
Population Health Sciences
University of Illinois Hospital and Health Sciences System
Chicago, Illinois, 60612
vprieto@uic.edu

Jerry A. Krishnan, MD/PhD
Population Health Sciences
University of Illinois Hospital and Health Sciences System
Chicago, Illinois, 60612
jakris@uic.edu

Bruce R. Schatz, PhD
Department of Medical Information Science
University of Illinois at Urbana-Champaign
Urbana, Illinois, 61801
schatz@illinois.edu

ABSTRACT

Detecting abnormal health is an important issue for mobile health, especially for chronic diseases. We present a free-living health monitoring system based on simple standalone smart phones, which can accurately compute walking speed. This phone app can be used to validate status of the major chronic condition, Chronic Obstructive Pulmonary Disease (COPD), by estimating gait speed of actual patients.

We first show that smart phone sensors are as accurate for monitoring gait as expensive medical accelerometers. We then propose a new method of computing human body motion to estimate gait speed from the spatio-temporal gait parameters generated by regular phone sensors. The raw sensor data is processed in both time and frequency domain and pruned by a smoothing algorithm to eliminate noise. After that, eight gait parameters are selected as the input vector of a support vector regression model to estimate gait speed. For trained subjects, the overall root mean square error of absolute gait speed is <0.088 m/s, and the error rate is <6.11%.

We design GaitTrack, a free living health monitor which runs on Android smart phones and integrates known activity recognition and position adjustment technology. The GaitTrack system enables the phone to be carried normally for health monitoring by transforming carried spatio-temporal motion into stable human body motion with energy saving sensor control for continuous tracking. We present validation by monitoring COPD patients during timed walk tests and healthy subjects during free-living walking. We show that COPD patients can be detected by spatio-temporal motion and abnormal health status of healthy subjects can be detected by personalized trained models with accuracy >84%.

The ACM Conference on Bioinformatics, Computational Biology, Biomedical Informatics (BCB) Health Information Symposium (HIS) September 25th, 2013 Washington DC, USA

Categories and Subject Descriptors

J.3 [**Computer Application: Life and Medical Sciences**]: Health

General Terms

Design, Experimentation, Measurement

Keywords

Gait Speed, Smart Phone Application, Chronic Disease Assessment, Free-living Health Monitoring

1. INTRODUCTION

Supporting Population Health requires detecting abnormal health situations and taking appropriate actions to effectively treat the patients [1]. "Gait speed" has been identified as the "sixth vital sign" [2] with significant clinical applications [3] and major longitudinal studies demonstrating strong correlation between gait speed and patient mortality [4]. Compared to other major vital signs, gait speed is a simple measure that can predict health status yet be computed using only embedded sensors of ordinary mobile devices.

Walk tests are widely applied in major chronic disease assessment as standard medical measures, such as Chronic Obstructive Pulmonary Disease (COPD) [5] and Congestive Heart Failure (CHF) [6], which afflict millions of patients and are major costs for Medicare. For these conditions, gait speed is again correlated with patient mortality, such as with the lung disease COPD [7]. Average gait speed can be easily computed within these tests since they are always conducted over a fixed distance or time. For example, the standard 6-minute walk test demands that the subject walks for six minutes back and forth over a measured distance in a hospital corridor while under the supervision of a nurse coordinator [8].

Kinesiology has long studied the biomechanics of human motion for gait analysis [9]. Generally there are two ways to recognize gait in medical studies which utilize expensive devices designed for specific medical tasks: Machine Vision Based [10] and Wearable Sensor Based [11]. Machine Vision Based gait analysis is monitored by expensive multi-camera systems which limit the walking space to small laboratories and prohibit the use in free-living conditions.

The latter approach is conducted with multi-sensors (generally pedometers and accelerometers) to gather multi-dimensional data while walking. Since wearable sensor based approach provides higher mobility, it has been applied in free-living health monitoring of COPD patients. Moy et al. [12] monitored everyday step count of COPD patients with a medical pedometer; while Pitta et al. [13] measured more complicated daily activity of COPD patients with expensive medical accelerometers.

A medical pedometer is today less expensive than a midrange smartphone (e.g. $20 versus $200), but less accurate for gait analysis. It must be fixed to the body, by being clipped to the belt, and the fixed nature of the embedded software uses a single walking algorithm to count steps, even when the daily activity is not good walking, such as walking up stairs or riding in cars. A phone app can support personalized models for gait analysis, using only relevant data from continuous monitors. A medical accelerometer is today more expensive than even a high-end smartphone (e.g. $6000 versus $600), but its extra power is not necessary for gait analysis. It must again be fixed to the body, usually strapped to the stable point in the small of the back, while measuring at a high sampling rate. But, as discussed below, human motion requires only a low sampling rate (5Hz versus 100Hz), which midrange phones can easily support for gait analysis, even while timesharing with other applications.

Zijlstra [14, 15] first discussed utilization of trunk accelerations to measure spatio-temporal gait parameters during human walking. This study showed that a lower trunk accelerometer is able to measure spatial and temporal gait parameters, even in unconstrained walking situations. Typical walking variations between older and younger subjects can be demonstrated by the analysis of spatio-temporal gait parameters. Trunk accelerometry has been utilized to demonstrate that severity of chronic diseases is strongly correlated with spatio-temporal gait parameters. Moreover, these studies show that human gait features (speed, gait cycle, cadence, etc.) are correlated to the spatio-temporal device motion (acceleration deviation, autocorrelation coefficient, root mean square, etc.).

Annegarn et al. [5] specifically investigate the spatio-temporal motion of trunk accelerometer for COPD patients via six-minute walk tests. The six-minute walk test is an efficient assessment of functional exercise performance of COPD patients, which becomes a major evaluation of the functional status of COPD patients. In this study, tri-axial accelerometers attached at the lower back were used to measure walking viability. The result shows that the severity of COPD patients is strongly correlated with their walking viability, which is reflected as the human gait parameters, as well as, the spatio-temporal motion of accelerometry.

Modern smart phones are ubiquitous and contain sophisticated sensors including global positioning systems (GPS) measuring latitude and longitude, tri-axial accelerometers measuring acceleration change in three dimensions, gyroscopes measuring rotational changes and magnetometers measuring orientation. WiFi and 4G-LTE networks support high speed data transmission between phones and servers. This comprehensive set of sensors combined with the computational power of the phone processors and highly expandable operating system provides an ideal platform to deploy widespread monitoring systems cheaply to the general population.

We have developed a phone app called GaitTrack, which can continuously measure gait speed in free-living conditions. We show that phone sensors are as accurate as medical accelerometers for measuring gait, that phone software is as accurate as physical measurements for walk tests with COPD patients, and that continuous health monitors for daily free-living walking can be implemented with smart phone applications.

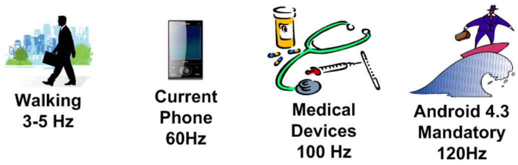


Figure 1: Sampling Frequencies for Standard Devices.

2. PHONE ACCURACY

It might be thought that phone sensors would not be adequate for medical tasks. However, the underlying physical MEMS accelerometer chips are often the same or have very similar operating characteristics in phones as in medical devices. The primary difference between phones and dedicated medical devices lies in the firmware of the device itself. While medical devices are designed to solely read the accelerometer sensor at a high frequency and record the results, phones are designed to conduct a myriad of tasks including reading sensors, taking phone calls, playing games, etc. and must handle multitasking each task in a fair manner. Thus, medical accelerometers excel at taking raw data at high frequencies but lack the capability to do computational tasks on the device while phones must take readings at lower frequencies to handle the multitasking but can do more computational correcting to the sensor readings on the device. Our phone app for gait analysis must be specially designed to utilize the phone's capabilities by implementing algorithms to pre-process data which correct for lower frequency sampling thereby maintaining the accuracy of the readings.

2.1 Sampling Frequency

One important consideration in designing a medical walk monitor is what sampling frequency is sufficient to capture a patient's gait accurately. Figure 1 shows the various frequency capabilities of modern devices. The upper-end of medically validated devices typically choose 100Hz. We believe the choice of 100Hz was not based upon prior research, but was arbitrarily chosen. Medical studies tend to put the required sampling frequency much lower at 3-5Hz [11]. To identify the frequency ranges with important signal information, we do the following experiment. We take measurements with an iPhone capable of attaining the medically accepted 100 Hz frequency readings. First, acceleration measurements are taken with the phone stationary. Then, a second set of measurements are taken with the same phone attached to the hip of a walking subject. These two measurements allow us to calculate the signal-to-noise ratio in order to determine how much actual good walking signal is present in the measurements.

Table 1 shows the results of the experiment. We first calculate the signal to noise ratio of -6.36 dB for our stationary versus walking signal. The gravity present in the noise signal along with the variance in the higher frequencies dominates the walking signal therefore making the signal-to-noise ratio very bad. In fact, there appears to be more noise than good signal. We then subtract the gravity constant and run both the stationary data and walking data through a 5 Hz low pass filter. The signal-to-noise ratio is then calculated at 6.31 dB demonstrating a strong amount of actual walking signal in the lower frequency data. Finally, we run the stationary

Filtering	S/N Ratio
None	-6.36 dB
Low Pass 5 Hz Filter	6.31 dB
High Pass 15 Hz Filter	-3.97 dB
High Pass 25 Hz Filter	-3.96 dB

Table 1: Signal-to-noise Ratios

Figure 2: Six Minute Walk Test with Smart Phone Taped to Medical Accelerometer Attached at Stable L3 Point.

and walking data through two high pass filters with a 15 Hz cutoff frequency and a 25 Hz cutoff frequency. The signal to noise ratio is -3.97 dB for the 15Hz signal and -3.96 dB for the 25 Hz filter. Thus, the substantial bulk of the walking signal is found in the lower bands and the higher frequency bands above 15 Hz primarily contribute noise to a high quality medical monitor and may be safely disregarded for use in further analysis.

Therefore, a monitoring frequency of 60Hz is more than sufficient to capture walking characteristics. Sixty hertz yields a Nyquist rate of 30Hz in the output signal. This creates a medical device capable of measuring signals that occur at thirty times a second, the same frequency that the average hummingbird beats its wings while in flight. While proponents of expensive medical devices may assert this as being too low, there is little medical evidence that such rapid movements are necessary to assess gait. It should be noted that while readings above 60 Hz are not useful, arguments against lowering the sampling frequency will be trivialized since the future Android standard for version 4.3 requires the devices maintain a 120 Hz sampling frequency for accelerometers. This standard is what midrange smartphones will support when our clinical trials are run with free-living walking, two years from now.

2.2 Accelerometer Sensor Pipeline

We design our software to actively measure the sampling rate of the accelerometer on an Android phone. As expected, the raw sampling rate varies over time due to processor allocation mostly within the range of 20-100Hz depending on processor load. Effective use of the data requires that the sampling rate be fixed to an effective value after a post-process. In our case, 60Hz is selected since it is the middle point of variation and it is high enough to sense all gait features we need[16]. For our fixed-rate post-processing, the program takes sensor reading at the maximum speed and fills a queue of sensor recording. A second thread spawns to pop values off the queue and generates samples at 60Hz. If one sample is recorded in a binning interval, the algorithm records it. If multiple samples are recorded in a binning interval, the samples are averaged. If an interval contains no samples, then the value of the previous and next interval are recorded and the missing values are filled in so the samples are linearly distributed between the known points.

We conducted the following experiment to compare phone based GaitTrack system with a medical accelerometer. The GaitTrack system was installed on a Samsung Galaxy Ace, a midrange Android smart phone, monitoring two subject walking back and forth on a thirty-meter corridor. The medical device is the Zephyr BioHarness (100Hz sampling), used in physiological, kinesiological and bio-medical monitoring. The subjects wear a belt on their waist which holds both the BioHarness and phone at the lower back, or the L3 position, known to be a stable point for monitoring walking[17] as shown in Figure 2. The BioHarness transmits readings to another smart phone via Bluetooth which then logs the data for further analysis.

	Galaxy Ace	BioHarness	Pearsons' r
PF	1.90(1.79-1.92)	1.97(1.86-2.00)	0.934
RMS	1.11(1.06-1.13)	1.14(1.09-1.16)	0.985
AC	0.863(0.761,0.926)	0.889(0.792-0.937)	0.935
CV	0.404(0.310-0.451)	0.396(0.294-0.443)	0.992

Table 2: Calculated Spatio-temporal Gait Parameters in Mean (Min-Max) Format. r Represents the Pearson's Correlation Coefficient.

Spatio-temporal gait parameters are calculated from the raw acceleration data. In this study, we selected four major gait parameters to make the comparison: peak frequency (PF), root mean square (RMS), autocorrelation coefficient (AC) and coefficient of variance (CV)[18]. Peak frequency is the frequency of the highest peak in the frequency domain which also indicates the periodicity of gait. The root mean square, autocorrelation coefficient and coefficient of variance are descriptions of signals in time domain. Generally, root mean square value is negatively related with the degree of gait stability. The autocorrelation coefficient indicates the balance of gait; a higher autocorrelation value indicates higher repeatability of gait cycles during a period of time[5]. Conversely, the coefficient of variance indicates the level of gait variability. Before computing all gait parameters, the raw data is processed with a low pass filter (<15Hz) to remove faster motion than human walking[11].

Totally, the two subjects walked for thirty six times back and forth on the thirty meter corridor, generating thirty six individual samples. We process the raw data for each sample and retrieve four spatio-temporal gait parameters as described above, using data from both the GaitTrack and BioHarness devices. The correlation coefficients were calculated between the two data sets as shown in Table 2. The results demonstrate a strong correlation between the data sets generated by the phone and the BioHarness. The correlation coefficients of PF, RMS, AC and CV are all greater than 0.90 while the RMS and CV are correlated at 0.985 and 0.992 respectively. Therefore, the raw output from the GaitTrack phone app with the smoothing algorithm is able to match the output of the BioHarness, a high performance medical device with an accelerometer.

3. FREE-LIVING HEALTH MONITOR

After proving the accelerometer integrated in a middle ranged phone performs as well as a medical accelerometer while measuring gait, we design a multi-level detection algorithm to allow the phone to serve as a health monitor during free-living movement. The framework of the free-living health monitor is presented in Figure 3. We first address the energy problems present while monitoring health continuously in Section 3.1. We show that with proper signal processing the phone sensor is able to detect "good walking" from the raw data of daily activities in Section 3.2. We conduct medical validation by concentrating on COPD severity which is strongly related to gait speed[5]. In Section 4, we attempt to build an estimator for gait speed via supervised-learning methods, in order to detect whether a subject has COPD. Finally, Section 5 discusses the effectiveness of detecting arbitrary abnormality of health status during free-living conditions.

3.1 Low Energy Walk Identification

We design a multi-level walk detection algorithm to allow the phone to go into a low-power screen off mode while still being able to measure walking continuously. We propose to accomplish this by noting that good walking necessitates the user be moving somewhere through space. Therefore, we expect that the signal strength of the wireless connection on the phone would therefore fluctuate

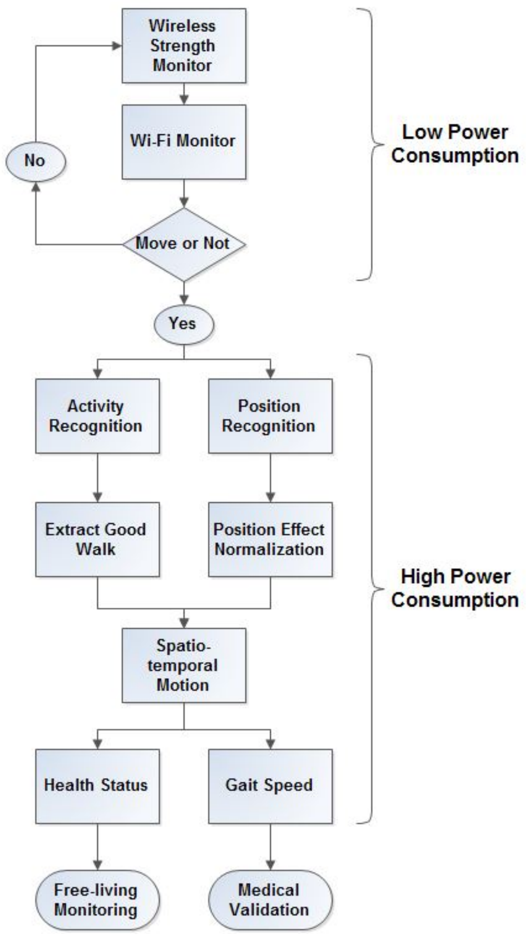


Figure 3: Free-living Health Monitor System

as the user moves past various obstacles. This requires very little power since a smart phone will be continuously connected to the wireless tower regardless if the user is monitoring gait. The algorithm will also opportunistically, monitor the signal strength of WiFi connections in the area. We recommend that the user turn on the WiFi in order to utilize the lower power gait detection algorithm. This idea uses the same principle as recent work using WiFi to improve GPS accuracy inside buildings, but is easier since we are only concerned with a binary decision of whether the phone is moving or not [19]. If the WiFi scan indicates motion, the phone will turn on the full accelerometer pipeline and begin taking readings for the walk activity recognition and gait classification which requires greater battery power and the screen locked in the "On" state.

To determine the power requirements of the various states of gait monitoring, we hook a multi-meter directly between a Samsung Galaxy Ace model 5830 smart phone and the 4.0 volt battery and measure the current drawn. The greatest power requirement seems to come from the screen on bright which draws roughly 400 milliwatts of power. Sleep mode draws an average of only 40 mW of power from the battery. Full walk recognition requires roughly 720 mW, a large enough power requirement that running it continuously would drain the battery prematurely. Contrarily, our wireless monitor only draws 240 mW primarily due to the extra overhead scanning the wireless networks which could be further reduced by increasing the times between scans. Still at 240 mW, the battery in the phone should last for $\frac{1500_{mAh}}{60_{mA}} = 25.0$ hours assuming no other use. This is a net decrease of 12.5 hours from the estimated time with screen off and WiFi on of $\frac{1500_{mAh}}{40_{mA}} = 37.5$ hours, but a large improvement to the cost of the walk recognition algorithm which would reduce battery life to a mere $\frac{1500_{mAh}}{180_{mA}} = 8.3$ hours.

3.2 Good Walking Computation

In free-living condition, good walking, defined as a comparatively long period of constant walking here, is only a small portion of daily activities. Thus, how to recognize good walking is a stepping stone for supporting gait analysis during free-living health monitoring. As soon as the phone is detected as moving, the monitoring system starts to collect raw sensor data. Then the first step in is to convert the low-level signals generated from the sensors into a high-level representation of the data in the form of feature vectors more effective for gait analysis.

To represent the spatio-temporal motion of human body from a phone based tri-axial accelerometer, the raw data in tri-axial coordinates is transformed to a horizontal-vertical body based coordinates, with the help of the gravity vector generated from the phone sensors as shown in Figure 4. To implement this coordinate transform, we first transform the three-dimensional coordinates to spherical coordinates. Let $F(\gamma_g, \theta_g, \varphi_g)$ and $F(\gamma_a, \theta_a, \varphi_a)$ represent the gravity vector and the acceleration vector, respectively. We know that in the objective coordinate system the gravity always directs to the negative vertical axis, known as $F'(\gamma_g', \theta_g', \varphi_g')$. Thus we have

$$\gamma_g' = \gamma_g \tag{1}$$

$$\theta_g' = \theta_g \tag{2}$$

$$\varphi_g' = 0 \tag{3}$$

$$\Delta\varphi = \varphi_g - \varphi_g' \tag{4}$$

it gives us the rotation of spherical coordinates. Also, because

$$\gamma_a' = \gamma_a \tag{5}$$

$$\theta_a' = \theta_a \tag{6}$$

$$\varphi_a' = \varphi_a - \Delta\varphi \tag{7}$$

we get the representation of acceleration in the new coordinates

$$F'(\gamma_a', \theta_a', \varphi_a') = F'(\gamma_a, \theta_a, (\varphi_a - \Delta\varphi)) \tag{8}$$

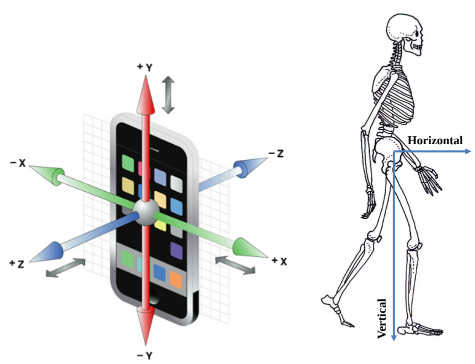


Figure 4: 3D coordinates of mobile devices and Body-based coordinates

When the new spherical coordinates are transformed back to Cartesian coordinates, we get the real gravitational component and horizontal component of the acceleration vector from the magnetometer sensor and the accelerometer sensor within the smart phone.

After the coordinate transform, Fourier's Transform is applied to smooth the acceleration curve. It has been demonstrated that human activities almost fall in the frequency range of 0-10Hz[20]. The signal-to-noise ratio taken on the samples above 15 Hz demonstrate that higher frequency components are primarily composed of noise and contain almost no actual contribution to the walking data. Thus we set a low pass filter in the frequency After taking the FFT, we simply clear the data of the frequency bands above 15 Hz before applying the inverse FFT to convert the signal back into the time domain. Thus, the higher frequency noise is removed before we compute spatio-temporal gait parameters.

With the above processing, the put-in direction of the phone will be normalized, and noise generated by higher frequency phone shaking will be eliminated as well. Thus even the phone is loosely carried, it works the same as tightly attached on the body.

3.3 Activity Recognition

Within a comparatively short period of data collection, different types of activities need to be detected to extract the part of good walking. There have been several studies presenting efficient classification algorithms of activity recognition[21,22,23,24,25]. Recently, Lu et al.[26] presented a high accuracy activity classification algorithm based on Nokia phone sensors. Here we represent the same algorithm using our own software to develop an effective activity recognition algorithm. Since we are only concerned about good walking, a binary classifier is good enough for monitoring health. However, we still build a classifier which separates movements into four major categories: stationary, walking, uneven and other. To avoid true negative error, the subject is required to walk in different speeds (slow, medium, fast) during the training period as shown in Table 3(a). The description and evaluation of activity recognition result is shown in Table 3(b).

(a) Types of Movements

Stationary	Sitting, Standing
Walking	Slow, Medium, Fast
Uneven	Up Hill, Upstairs, Downstairs
Other	Jogging, Cycling, Vehicle

(b) Evaluation

Category	Accuracy
Stationary	1.0000
Walking	0.9978
Uneven	0.9630
Other	0.9909

Table 3: Movements Classification. Tested with 2 subjects (one young male and one old male.)

3.4 Position Recognition

Activity recognition must take into account the position of the phone on the user to maintain high accuracy. Position recognition of mobile devices is claimed to be possible by recent studies[27]. The accuracy of position detection is higher than 90%, which means with good training, it is easy to tell where the phone is carried using phone sensor data. For health monitoring, it is straightforward to know exactly where the phone is carried if we can find an adjustment to get a canonical gait vector. We operate an experiment that let the subject put phones in several normal carry-on positions, as well as fix at the L3 position, comparing the generated spatio-temporal gait parameters. Three different positions are selected in this experiment: pants pocket, coat pocket and handbag, which are the ordinary positions people carry their phones.

We computed the eight spatio-temporal gait parameters which are the features in our gait speed prediction model as presented in Section 4.1.1. To adjust features calculated from ordinary positions to a standard validation data, we use a linear regression model. We get a weight vector β_p and an intercept vector ε_p. For each feature f, the original value is x_{if}. The adjusted value is presented in (9).

$$x'_{if} = \beta_{pf}^T x_{if} + \varepsilon_p \tag{9}$$

The results show that spatio-temporal gait parameters from generated different position are correlated with the L3 stable point as shown in Table 4. In the table, the confidence interval (*CI*) of each weight coefficient is presented. The results show that except for 3 outliers (MeanAcc, AC for coat pocket and AC for pants pocket), all other spatio-temporal gait features for three ordinary positions can be adjusted to a stable L3 position with high confidence ($p < 0.05$). Thus, a linear model can be used to normalize the gait parameters and effectively remove the effects of positioning of the phone.

3.5 Spatio-Temporal into Body Motion

To compute walking patterns, the spatio-temporal motion has to be transformed into body motion. Cadence, the steps taken per minute, is an important feature to measure gait. The first step of using phone to compute gait is to count steps, functioning as a pedometer. Digital pedometers have been applied in gait tracking for years, especially in free-living due to its low cost. We provide an algorithm for step counting using the "good walking" data from the phone, more accurate than Omron HJ-720ITC, a commercial medical pedometer which is commonly used in COPD daily tracking[12].

Zijstra and Hof[14] implement a basic step counting algorithm over accelerometer by detecting zero crossing. However, any noise in the raw data will affect zero crossing so that the accuracy decreased. Computing the variation of sliding windows increases noise tolerance of step counting[28]. With previous knowledge that human stepping frequency is basically within 15Hz, we set an additional low pass filter in frequency domain as pre-processing. Thus, our step counting algorithm is shown in Algorithm 1.

The step counting algorithm is validated by compared to an Omron HJ-720ITC pedometer[29]. 2 subjects (1 young male and 1 old male) are involved in the validation, carrying the phone and the

	Linear Model Coefficients		
Feature	Pants Pocket	Coat Pocket	Handbag
MeanAcc	$**$	$-$	$**$
StdAcc	$***$	$***$	$***$
MCR	$***$	$***$	$***$
AC	$-$	$-$	$*$
CV	$***$	$***$	$***$
RMS	$***$	$**$	$***$
PF	$***$	$***$	$***$
Entropy	$*$	$***$	$**$

Table 4: Linear Model Evaluation for Position Adjustment. $***$**:**$p < 0.001$**;** $**$**:**$p < 0.01$**;** $*$**:**$p < 0.05$**;** $-$**:**$p > 0.05$

Algorithm 1 Step Counting Algorithm

```
X ← FFT on the RawData;
Y ← LowPassFilter(X, 15Hz);
Z ← Inverse FFT on Y;
HighPassFilter(Z,Mean(Z));
Initialize(W);
while i < length(Z)-WindowSize do
    region=Z[i:(i+WindowSize)];
    add Variance(region) to W[i];
    i++;
MinPeak ← ∞;
for each cycle c in W do
    MinPeak=Min(MinPeak,Max(c));
Initialize(L);
for (i = 1; i<length(W); i++) do
    L[i]= W[i]>MinPeak?1:0;
    if W[i-1]==1 && W[i]==0 then
        Count++;
return Count;
```

pedometer simultaneously and walking for 500 steps. The result shows that the absolute error rate of the phone algorithm is 0.012; while the error rate of pedometer is 0.052. Additionally, we can easily detect when the subjects are walking in free-living condition. With the time stamps phone provided along with the acceleration data, cadence is computed. Thus, our phone system is better than pedometers not only for higher step counting accuracy, but also because it computes cadence only during good walking periods.

To attempt medical validation of cadence computation, six subjects (three COPD patients and three healthy subjects) were tested with IRB approval. Each subject completed a session of six-minute walk test, while cadence is computed from phone sensors. The result compares the cadence between COPD patients and healthy subjects, shown in Table 5. The average cadence, maximum cadence and minimum cadence of COPD patients are lower than those of healthy subjects. Since it is known that digital pedometers undercount the steps of COPD patients[30], due to their cadence being slower than the fixed calibration of these devices, our phone app is a superior health monitor.

	COPD patients	Healthy Subjects
Average Cadence	49.6	60.0
Standard Deviation	9.3	9.2
Maximum	61.5	79.5
Minimum	36.0	51.7

Table 5: Cadence Comparison of COPD versus Healthy Subjects (steps/min)

4. GAIT SPEED ESTIMATION

Gait speed is a significant vital sign[2] for measuring health. One major strategy of accelerometer based gait speed estimation is calculating the product of cadence and stride length[17]. Thus, these methods are usually separated in to two independent steps: gait cycle extraction and stride length computation[31]. Each step may introduce computational errors in estimation of gait speed. As previously discussed, none of the current cadence computation methods can guarantee absolute accurate step counting even though the device is tightly fixed on the L3 position. With phones, the accuracy will be even lower if we want the phone to be put in its normal carrying positions, such as pants pocket. Conversely, the computation of stride length is based on an ideal triangle model, assuming that the legs form an isosceles triangle so that the step length is computable when the leg length l and step angle θ[32, 31, 16], which is highly inaccurate.

Recently, machine learning and regression models have been used in gait speed estimation. Vathsangam et al.[20] demonstrated that Gaussian process based regression can predict gait speed using sensor data from a belt worn tri-axial accelerometer. Alternatively, hand held medical devices have also been applied to estimate gait speed and with error rates of 12-15%[27]. However, machine learning methods are hard to interpret since the input features have no actual meaning. In this paper, we utilize the support vector machine (SVM), a typical machine learning method, in gait speed estimation[33]. For better interpretation and explanation, the features selected as input vectors for SVM are not from the raw acceleration but from real spatio-temporal gait features which have been proven to be correlated with human health[18].

4.1 Methodology

We have also designed and implemented an effective algorithm for detecting the turns so that the walk test data can be divided into lap length "good walking" samples. Our algorithm is based on two important insights: first, the amplitude at and around the turns is significantly smaller than while walking; second, two consecutive turns are not likely to happen in close proximity. According to these insights, our algorithm first transforms the raw walking data into the smoothed time-amplitude series. After that, rough regions of the turns are estimated by a peak finding algorithm. Finally, the number of turning points during the six minute walk period is identified by incorporating the proximity constraints.

4.1.1 Feature Computation

Previous work shows that the previously mentioned four spatio-temporal gait parameters, peak frequency (PF), root mean square (RMS), autocorrelation coefficient (AC) and coefficient of variance (CV), are strongly correlated to gait speed and human health[18, 34]. In addition, four other basic features of motion description are selected; mean of acceleration (MeanAcc), standard deviation of acceleration (StdAcc), mean crossing rate (MCR) and entropy of acceleration spectrum in frequency domain[26]. Totally eight features are selected and computed as the input vector of the support vector machine model to estimate gait speed.

4.1.2 Model Construction

One of the open-source R Support Vector Machine package (package e1071) is applied in model construction[35]. We utilize the Fisher linear kernel for the selected gait features in order to construct an eps-support vector regression model[36].

$$f(x_i) = \sum_{j=1}^{l} \alpha K(x_i, x_j) + b \tag{10}$$

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j) \tag{11}$$

Equation (10) demonstrate how the model is constructed, where x_i is a feature vector and $K(x_i, x)$ is the kernel function. The regression output is α, while b represents the noise vector. When a linear function is applied, $K(x_i, x)$ is shown as Equation (11).

Then refer to the position adjustment, Equation 9, the adjusted regression model function is (12) and the linear kernel is (13).

$$f(x_i) = \sum_{i=j}^{l} \alpha K(\beta_p^T x_i + \varepsilon_p, \beta_p^T x_j + \varepsilon_p) + b \quad (12)$$

$$K(\beta_p^T x_i + \varepsilon_p, \beta_p^T x_j + \varepsilon_p) = \phi(\beta_p^T x_i + \varepsilon_p)^T \phi(\beta_p^T x_j + \varepsilon_p) \quad (13)$$

4.2 Medical Validation

4.2.1 Experimental Setup

We implemented the gait monitoring system to operate a six minute walk test using the phone app shown in Figure 5 running on a Samsung Galaxy Ace. The program runs for six minutes, giving voice and vibrating instruction to guarantee a real six minute walk test environment, recording sensor data at 60Hz, as well as recording real time heart rate and blood oxygen level via Bluetooth connected pulse oximeter during the test. The program computes strides taken during the test and estimated walking distance with a pre-calibrated stride length. The results, as well as the raw sensor data, are securely archived and transmitted back to our server for further analysis.

With IRB approval, six COPD patients (five females, three mild COPD and two moderate COPD, and one male) from the University of Illinois Hospital and Health Sciences System in Chicago and six healthy subjects (three females and three males) from University of Illinois at Urbana-Champaign participated in our study. The walking data for the COPD patients was collected during a standard medical six-minute walk test[8] is operated for each individual, with observation and instruction of the nurse. All patients walked along a 15.24 meters (50 feet) corridor back and forth in the clinic, while all healthy subjects walked along a 30 meters (98 feet) corridor back and forth in the laboratory. Shoes and clothes during the test does not affect their gait and medical measurement.

4.2.2 Model Evaluation

Each subject did accomplish a full six-minute walk test. Since subjects walked along a flat corridor with a self-chosen speed without being interrupted during the walk test, which is classified as "good walk" except for the turns, we select each lap of the walk test as the sampling unit so that each sample only contains straight walking along a fixed length of walkway. The average walking speed for each lap, calculated by phone program, is regarded as the label of each sample. Totally 168 samples (83 healthy and 85

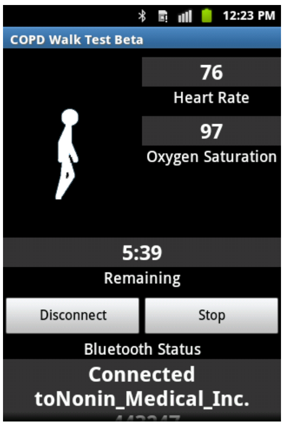


Figure 5: GaitTrack V2 Phone App

	E_{RMS} (m/s)	ER
Personalized	0.032	2.13%
Unified	0.088	6.11%
Cross Validation	0.133	9.98%

Table 6: Evaluation of SVM Model. E_{RMS}: Root mean square error. ER: Standard error rate of gait speed prediction.

COPD) were collected. Three different ways of validation are applied to evaluate the support vector regression model: personalized training, leave one out and cross validation within subjects as shown in Table 6.

First, we train a personalized model for each subject, and evaluate each model by leave one out validation. The root mean square error (E_{RMS}) between the predicted and actual gait speed is $0.032m/s$ and the standard error rate is 2.13%. Secondly, we constructed a unified model by leaving one sample out each trial. The root mean square error is $0.088m/s$ and standard error rate is 6.11%. After that, we want to know whether the gait speed is predictable when features of this subject do not contribute to the model training. Thus we evaluate the unified model by cross validation within subject, by leaving one entire subject out of the dataset while training then validating the model on that subject's data, instead of leave one sample out. This test produces root mean square error is $0.133m/s$ and standard error rate is 9.98%.The comparison between actual gait speed and predicted gait speed is presented in Figure 6.

Table 7 is the comparison of our model to several recent studies. The comparison shows that our model is better than the previous ones in prediction accuracy. Mannini *et al.*[33] implemented cascading SVM gait speed estimators both by individual training and trunk training. The root mean square error of individual training is 0.28km/h, which is 0.08m/s; while the root mean square error of the trunk training is 0.70km/h, which is 0.19m/s. Park *et al.*[27] implemented a regularized least squared (RLS) model to estimate gait speed. The overall root mean square error is 0.098m/s, while the root mean square error increases to 0.154m/s when the test subjects do not participate in training.

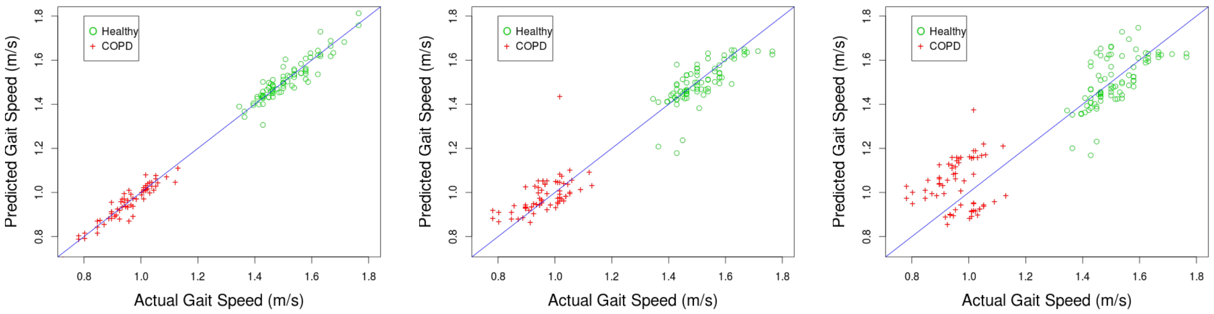
E_{RMS} (m/s)	SIG-SVM	c-SVM	RLS
Personalized	0.032	0.077	-
Unified	0.088	0.194	0.098
Cross Validation	0.133	-	0.154

Table 7: Comparison of Different Models for Gait Speed Estimation. SIG-SVM: Our SVM model with signal processing in feature selection. c-SVM: cascading SVM by Mannini *et al.*[33]. RLS: Regularized Least Square implemented by Park *et al.*[27]

Moreover, the standard six-minute walk test brings in 12.5% error for distance/speed evaluation due to the variation of walkway length, turning times and other factors[37]. Thus, gait speed estimation model with error of less than 6.11%, given some training, is more accurate with automatic phone software than with manual walkway tests.

5. FREE-LIVING ABNORMAL HEALTH

In free-living condition, the health monitor must be able to detect "abnormal health". Generally, abnormal health is defined as the deviation from the "normal range"[38]. The normal range of health varies in different cases. In COPD, severity levels are used to reflect abnormality. With healthy persons, there is no strict definitions on "normal" and "abnormal" gait, but for each individual, it is not hard



(a) Personalized Model (b) Leave-one-out (c) Cross Validation

Figure 6: Comparison between actual gait speed and predicted gait speed. Green circles represent healthy subjects and red crosses represent COPD patients. COPD (Abnormal) and Healthy (Normal) subjects are clearly distinguished by speed.

to define a overall normal range of health. Thus any deviation from this normal range can be regarded as "abnormal"[9].

5.1 Normal and COPD

Since the previous work shows that gait speed is strongly correlated with health status (Healthy or COPD) in free-living condition, we attempt to detect health status from the spatio-temporal gait parameters directly. First, we train the model with walk test data of six healthy subjects and six COPD patients as we did in gait speed estimation. Here we select a support vector machine[33] and a C4.5 decision tree[27] as the learning methods to train the classifier and make comparison. We evaluate the models by leave one out and cross validation within subjects. The evaluation result is shown in Table 8. The classification of healthy and COPD subjects is absolutely correct. The result indicates a high quality of our models in classifying healthy subjects and COPD patients.

	SVM (Accuracy)	C4.5 (Accuracy)
Leave-one-out	1.000	1.000
Cross Validation	1.000	1.000

Table 8: classification result for health subjects and COPD patients. Here Accuracy=$(N_{true\_healthy} + N_{true\_unhealthy})/N_{ALL}$

Subject	Gender	Age	Body Size	Abnormality
Subject MYS	Male	Young	Small	Vertebra Hurt
Subject MYM	Male	Young	Medium	Ankle Injury
Subject MYL	Male	Young	Large	Tiredness
Subject MOM	Male	Old	Medium	Back Injury
MYM2	Male	Young	Medium	N/A
FYS1(twin)	Female	Young	Small	N/A
FYS2(twin)	Female	Young	Small	N/A
FOS	Female	Old	Small	N/A
FOM	Female	Old	Medium	N/A
FOL	Female	Old	Large	N/A

Table 9: Free-Walking Subjects. Age varying from *"Young"*, defined in range of 20-29 years old, to *"Old"*, defined in range of 50-59 years old.

	SVM (Accuracy)	C4.5 (Accuracy)
Personalized Model	0.842	0.890
Unified Model	0.758	0.819

Table 10: Result of Free-living Abnormal Health Detection. Here Accuracy=$(N_{true\_healthy} + N_{true\_unhealthy})/N_{ALL}$

5.2 Individual Abnormal Health

To monitor individual abnormal health in free-living condition, we collected data from ten normal healthy subjects, demographically varying in age, sex and body sizes, each participating for around one week. This study was not an Android phone app, but a simulation of one using an existing iPhone app. The subjects were asked to walk for ten minutes each day with an iPhone carried in their pants pockets using *SensorData*, a commercial software app on iOS. Some subjects used an iPod Touch, which has the same sensors as the iPhone. Abnormal health status happened for four of our subjects with the others only healthy during the period as shown in Table 9. The collected data is split into equal-length pieces (1000 sample points each). Spatio-temporal gait parameters are calculated as presented in Section 4.1.1.

Since there are only four subjects with abnormal health status, we concentrate on detecting the health differentiation for these subjects. Two strategies are applied in building a classification model for detecting abnormal health: personalized training (train models for each individual with their own data) and unified training (train a single model for all subjects with the whole dataset). The complete system may integrate these two strategies to train the model with a minimized group of people and apply it to the whole population. We use the eight calculated spatio-temporal gait parameters as input. Support vector machine and C4.5 decision tree are applied to build classification models. Models are evaluated by leave one sample out. The result is presented in Table 10. The results show that abnormal health can be roughly detected by the applied models. When utilizing a personalized model trained by daily ten minute sessions for a week, the accuracy is higher than 84.2%. When utilizing a unified model, the accuracy is higher than 75.8%.

5.3 Future Work

The next stage of our research is to combine all of our existing components into a fully-fledged free-living health monitoring system with smart phones. We will develop an integrated system, encompassing energy conservation, activity recognition, and position adjustment as initial preparation for extracting good walking data from daily activities with continuous monitoring. This will be used for experiments in future work. Additionally, physiology data will be collected during tests for future correlations including oxygen saturation using pulse oximeters and heart rate variation using a chest strap monitor.

To train the gait model, we will collect free-living walking of healthy subjects and show that their abnormal health is detectable directly by spatio-temporal motion of smart phones carried in customary positions. This will help determine whether the model need to be trained individually, or can be trained for larger groups. If individually, we will determine the minimum training for a reliable detection model so that the system can be applied with the least training.

To demonstrate the utility of the complete GaitTrack system, it will be used to assess more subjects. Under approval of a new IRB in progress, we plan to assess 80 unhealthy (chronic disease) patients, with walk tests and with free walking, as well as several healthy subjects for comparison. This will enable us to determine how many patients must be tested, to evaluate the validity of our phone app across sex and age and severity. We will then design and implement a clinical trial to assess health status for the major chronic condition COPD, across the full range of demographic variation.

6. CONCLUSION

This study presents a health monitor system based on simple standalone phones and separately discusses each module of the system, concentrating on two major issues: gait speed estimation in a timed walk test and free-living abnormal health detection. The former is to match medical validation and the latter is to apply spatio-temporal motion in daily life.

Subjects in our experiments vary in age, sex and body size. Our walk test result shows that gait speed of healthy subjects varying in age and sex has comparatively small variation range when compared to the variation between healthy subjects and COPD patients. The reason for this is that walking for six minutes is beyond the fitness tolerance of COPD patients so they have to slow down to finish it; while healthy people, even old people, can easily accomplish this test. Thus, in gait speed estimation, we assume that the effect of demography is a minor factor; oppositely, the COPD severity is the major effect of gait speed.

We select several supervised learning methods to construct models. It means not only the methodology, but also the size of training dataset determines the quality of models. Although the study size at present is small, the root mean square error of gait speed estimation is limited to 9.98% evaluated by untrained subjects, which is still better than results (12%-15%) of current related work, which uses medical accelerometers[27]. As noted, our results show our estimation error rate decreased even more, half as much as the results of previous work, when the subject's data contribute to model training.

For a free-living health monitor, we construct classification models from spatio-temporal motion to detect health status. The abnormal health here stands for any deviation from the normal health range. In specific situations, the binary classification on healthy or unhealthy can be modified to a multi-category classification. For example, to measure COPD severity, the categories can be severity levels of COPD (healthy, mild, moderate, severe). Or to measure daily living as in our pilot studies with phone apps, the categories can be well or sick, energetic or tired, happy or sad.

Medical literature shows that gait is able to assess major chronic diseases like COPD (lung disease) and CHF (heart disease). Gait speed can be effectively measured by medical accelerometers, but their expense limits the population that can use them. Healthcare costs prohibit medical devices as monitors for the millions of patients with COPD and CHF, but nearly all currently have mobile phones. Within four years, the cheapest mobile phone will have the same sensor capability as the current smart phone.

We have demonstrated that simple smart phones have the ability to measure gait as accurately as expensive medical devices. Gait speed can be predicted from the phone sensor data, with proper spatio-temporal motion computation. The experiment with both healthy subjects and COPD patients clearly shows that after preprocessing of the raw sensor data, a support vector machine is able to construct a model for accurate gait speed prediction. Medical literature shows that COPD patients walk slower than healthy people for a comparatively long distance. Thus, simple phones can continuously monitor chronic disease to validly predict COPD severity.

7. ACKNOWLEDGEMENTS

All patient data collected from six-minute walk tests and gait monitoring phone sensors are protected under the University of Illinois at Chicago IRB approved protocol # 2011-0625, as part of the Pulmonary Research Registry, through the Hospital and Health Sciences System. Thanks to Nina Grude, RN, for help with testing patients. This research was funded in part by USDA National Research Initiatives epidemiology grant 2008-04074, with Bruce Schatz as PI. The Health Information Technology Center at the University of Illinois at Urbana-Champaign provided additional student support and seed funds. The Institute for Genomic Biology provided computing and building facilities for software development and technology evaluation.

References

[1] B. R. Schatz and R. B. Berlin, *Healthcare Infrastructure: Health Systems for Individuals and Populations*. Series in Health Informatics. Springer London Limited, 2011.

[2] S. Fritz and M. Lusardi, "White paper: Walking speed: The sixth vital sign.," *Journal of Geriatric Physical Therapy*, vol. 32, no. 2, p. 2, 2009.

[3] S. Studenski, "Bradypedia: is gait speed ready for clinical use?," *The Journal of Nutrition, Health & Aging*, vol. 13, no. 10, pp. 878–880, 2009.

[4] S. Studenski, S. Perera, K. Patel, C. Rosano, K. Faulkner, M. Inzitari, J. Brach, and et al., "Gait speed and survival in older adults," *J American Medical Association JAMA*, vol. 305, pp. 50–58, 2010.

[5] J. Annegarn, M. A. Spruit, H. H. Savelberg, P. J. Willems, C. v. d. Bool, A. M. Schols, E. F. Wouters, and K. Meijer, "Differences in walking pattern during 6-min walk test between patients with copd and healthy subjects," *PLOS ONE*, vol. 7, no. 5, p. e37329, 2012.

[6] M. Jehn, A. Schmidt-Trucksäess, T. Schuster, H. Hanssen, M. Weis, M. Halle, and F. Koehler, "Accelerometer-based quantification of 6-minute walk test performance in patients with chronic heart failure: applicability in telemedicine," *Journal of Cardiac Failure*, vol. 15, no. 4, pp. 334–340, 2009.

[7] C. Casanova, C. Cote, J. M. Marin, V. Pinto-Plata, J. P. de Torres, A. Aguirre-Jaíme, C. Vassaux, and B. R. Celli, "Distance and oxygen desaturation during the 6-min walk test as predictors of long-term mortality in patients with copd," *CHEST Journal*, vol. 134, no. 4, pp. 746–752, 2008.

[8] American Thoracic Society, "ATS statement: Guidelines for the six-minute walk test," *American Journal of Respiratory and Critical Care medicine*, vol. 166, no. 9, pp. 111–117, 2002.

[9] M. Whittle, *Gait Analysis: An Introduction*. Butterworth Heinemann Elsevier, 4th ed., 2007.

[10] T. Moeslund, A. Hilton, and V. Krüger, "A survey of advances in vision-based human motion capture and analysis," *Computer Vision and Image Understanding*, vol. 104, no. 2, pp. 90–126, 2006.

[11] R. LeMoyne, C. Coroian, T. Mastroianni, and W. Grundfest, "Accelerometers for quantification of gait and movement disorders: a perspective review," *Journal of Mechanics in Medicine and Biology*, vol. 8, no. 02, pp. 137–152, 2008.

[12] M. L. Moy, N. A. Weston, E. J. Wilson, M. L. Hess, and C. R. Richardson, "A pilot study of an internet walking program and pedometer in copd," *Respiratory Medicine*, 2012.

[13] F. Pitta, T. Troosters, V. Probst, M. Spruit, M. Decramer, and R. Gosselink, "Quantifying physical activity in daily life with questionnaires and motion sensors in copd," *European Respiratory Journal*, vol. 27, no. 5, pp. 1040–1055, 2006.

[14] W. Zijlstra and A. L. Hof, "Assessment of spatio-temporal gait parameters from trunk accelerations during human walking," *Gait & Posture*, vol. 18, no. 2, pp. 1–10, 2003.

[15] W. Zijlstra, "Assessment of spatio-temporal parameters during unconstrained walking," *European Journal of Applied Physiology*, vol. 92, no. 1-2, pp. 39–44, 2004.

[16] M. Yang, H. Zheng, H. Wang, S. McClean, and N. Harris, "Assessing the utility of smart mobile phones in gait pattern analysis," *Health and Technology*, vol. 2, no. 1, pp. 81–88, 2012.

[17] R. Moe-Nilssen and J. L. Helbostad, "Estimation of gait cycle characteristics by trunk accelerometry," *Journal of Biomechanics*, vol. 37, no. 1, pp. 121–126, 2004.

[18] S. Nishiguchi, M. Yamada, K. Nagai, S. Mori, Y. Kajiwara, T. Sonoda, K. Yoshimura, H. Yoshitomi, H. Ito, K. Okamoto, and et al., "Reliability and validity of gait analysis by android-based smartphone," *Telemedicine and e-Health*, vol. 18, no. 4, pp. 292–296, 2012.

[19] Y. Jiang, X. Pan, K. Li, Q. Lv, R. P. Dick, M. Hannigan, and L. Shang, "Ariel: Automatic wi-fi based room fingerprinting for indoor localization," in *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, pp. 441–450, ACM, 2012.

[20] H. Vathsangam, A. Emken, D. Spruijt-Metz, and G. S. Sukhatme, "Toward free-living walking speed estimation using gaussian process-based regression with on-body accelerometers and gyroscopes," in *Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, pp. 1–8, IEEE, 2010.

[21] E. Tapia, S. Intille, and K. Larson, *Activity recognition in the home using simple and ubiquitous sensors*. Springer, 2004.

[22] J. Yang, J. Wang, and Y. Chen, "Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers," *Pattern Recognition Letters*, vol. 29, no. 16, pp. 2213–2220, 2008.

[23] J. Yang, "Toward physical activity diary: motion recognition using simple acceleration features with mobile phones," in *Interactive Multimedia for Consumer Electronics*, pp. 1–10, ACM, 2009.

[24] L. Sun, D. Zhang, B. Li, B. Guo, and S. Li, "Activity recognition on an accelerometer embedded mobile phone with varying positions and orientations," in *Ubiquitous Intelligence and Computing*, pp. 548–562, Springer, 2010.

[25] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," *ACM SIGKDD Explorations Newsletter*, vol. 12, no. 2, pp. 74–82, 2011.

[26] H. Lu, J. Yang, Z. Liu, N. D. Lane, T. Choudhury, and A. T. Campbell, "The Jigsaw continuous sensing engine for mobile phone applications," in *Embedded Networked Sensor Systems*, pp. 71–84, ACM, 2010.

[27] J. Park, A. Patel, D. Curtis, S. Teller, and J. Ledlie, "Online pose classification and walking speed estimation using handheld devices," in *Ubiquitous Computing*, pp. 113–122, ACM, 2012.

[28] S. Zhong, L. Wang, A. M. Bernardos, and M. Song, "An accurate and adaptive pedometer integrated in mobile health application," in *Wireless Sensor Network, (IET-WSN)*, pp. 78–83, IET, 2010.

[29] E. Holbrook, T. Barreira, M. Kang, *et al.*, "Validity and reliability of Omron pedometers for prescribed and self-paced walking," *Medicine+ Science in Sports+ Exercise*, vol. 41, no. 3, p. 670, 2009.

[30] L. J. Turner, L. Houchen, J. Williams, and S. J. Singh, "Reliability of pedometers to measure step counts in patients with chronic respiratory disease," *Journal of Cardiopulmonary Rehabilitation and Prevention*, vol. 32, no. 5, pp. 284–291, 2012.

[31] S. Chen, C. L. Cunningham, J. Lach, and B. C. Bennett, "Extracting spatio-temporal information from inertial body sensor networks for gait speed estimation," in *Wearable and Implantable Body Sensor Networks*, pp. 71–76, IEEE, 2011.

[32] S. Miyazaki, "Long-term unrestrained measurement of stride length and walking velocity utilizing a piezoelectric gyroscope," *IEEE Transactions on Biomedical Engineering*, vol. 44, no. 8, pp. 753–759, 1997.

[33] A. Mannini and A. M. Sabatini, "On-line classification of human activity and estimation of walk-run speed from acceleration data using support vector machines," in *Engineering in Medicine and Biology Society (EMBC)*, pp. 3302–3305, IEEE, 2011.

[34] M. Yamada, T. Aoyama, S. Mori, S. Nishiguchi, K. Okamoto, T. Ito, S. Muto, T. Ishihara, H. Yoshitomi, and H. Ito, "Objective assessment of abnormal gait in patients with rheumatoid arthritis using a smartphone," *Rheumatology international*, vol. 32, no. 12, pp. 3869–3874, 2012.

[35] C. Chang and C. Lin, "Libsvm: a library for support vector machines," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 2, no. 3, p. 27, 2011.

[36] V. N. Vapnik, "An overview of statistical learning theory," *IEEE Transactions on Neural Networks*, vol. 10, no. 5, pp. 988–999, 1999.

[37] S. S. Ng, P. C. Yu, F. P. To, J. S. Chung, and T. H. Cheung, "Effect of walkway length and turning direction on the distance covered in the 6-minute walk test among adults over 50 years of age: a cross-sectional study," *Physiotherapy*, vol. 99, no. 1, pp. 63 – 70, 2013.

[38] I. Pilowsky, "A general classification of abnormal illness behaviours," *British Journal of Medical Psychology*, vol. 51, no. 2, pp. 131–137, 1978.