

UPTIME: Ubiquitous Pedestrian Tracking using Mobile Phones

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Abstract—The mission of tracking a pedestrian is valuable for many applications including walking distance estimation for the purpose of pervasive healthcare, museum and shopping mall guides, and locating emergency responders. In this paper, we show how accurate and ubiquitous tracking of a pedestrian can be performed using only the inertial sensors embedded in his/her mobile phone. Our work depends on performing dead reckoning to track the user’s movement. The main challenge that needs to be addressed is handling the noise of the low cost low quality inertial sensors in cell phones. Our proposed system combines two novel contributions: a novel step count estimation technique and a gait-based accurate variable step size detection algorithm.

The step count estimation technique is based on a lightweight finite state machine approach that leverages orientation-independent features. In order to capture the varying stride length of the user, based on his changing gait, we employ a multi-class hierarchical Support Vector Machine classifier. Combining the estimated number of steps with the an accurate estimate of the individual stride length, we achieve ubiquitous and accurate tracking of a person in indoor environments.

We implement our system on different Android-based phones and compare it to the state-of-the-art techniques in indoor and outdoor testbeds with arbitrary phone orientation. Our results in two different testbeds show that we can provide an accurate step count estimation with an error of 5.72%. In addition, our gait type classifier has an accuracy of 97.74%. This leads to a combined tracking error of 6.9% while depending only on the inertial sensors and turning off the GPS sensor completely. This highlights the ability of the system to provide ubiquitous, accurate, and energy efficient tracking.

Keywords-Inertial navigation; mobile phone tracking; step count estimation; stride length estimation; ubiquitous indoor localization;

I. INTRODUCTION

Nowadays, mobile phones have become true ubiquitous computing devices that are in widespread use by most persons around the globe, even in developing countries. During the last decade, mobile phones have been witnessing many improvements in their computing power, memory size, and the number of sensors embedded in the device (e.g. GPS, accelerometer, magnetometers). Meanwhile, location-based services (LBS) have also been gaining an increasing focus. Most of those applications depend on either using GPS or network (GSM or WiFi)-based localization techniques to estimate the user’s location. However, although GPS can

provide an accurate estimate for the user’s location, it is an energy hungry technology that can drain the limited phone battery quickly and it does not work in areas with no line-of-sight to the satellites, especially indoors. On the other hand, although GSM and WiFi based localization techniques are more energy efficient [1], [2], [3] and can work in both outdoor and indoor environments, their accuracy is much more coarse grained, which limits their set of applications, and they require a tedious radiomap construction phase.

Recently, techniques that leverage the embedded inertial sensors in cell phones (e.g. accelerometers, magnetometers, and gyroscopes) have been proposed, e.g. [4], [5], as energy efficient and ubiquitous tracking systems. The main idea is to use dead reckoning (DR) [6] to obtain the user’s location by combining an initial known position with the displacement estimated using the inertial sensors. However, these techniques assume a fixed phone orientation, which is far from the typical case, where the phone can be placed in the user’s pocket or purse.

In this paper, we present UPTIME: (Ubiquitous Pedestrian Tracking usIng Mobile phonEs) as an accurate and ubiquitous tracking system based on dead reckoning. To handle the effect of the noisy sensors, UPTIME estimates the displacement by combining two novel contributions: a step boundary estimation module and a step size estimation module¹. The step boundary estimation module is based on a lightweight finite state machine (FSM) approach that leverages orientation-independent features. In order to capture the varying stride length of the user, based on his changing gait, we employed a multi-class hierarchical Support Vector Machine (SVM) classifier based on a novel combination of features to classify a detected step into one of three classes: walking, jogging, or running. This is used to provide a more accurate estimate for the stride length of the step.

To evaluate our system, we implement it on Android-based phones and compare it to the state-of-the-art techniques. Our results in indoor and outdoor testbeds with arbitrary phone orientation show that we can provide an accurate step count estimation with an error of 5.72%. In

¹Previous work in dead reckoning using mobile phones, e.g. [7], [8], considers the stride length of each step to be constant.

addition, our gait type classifier has an accuracy of 97.74%. This leads to a combined tracking error of 6.9% while depending only on the inertial sensors and turning off the GPS sensor completely.

The rest of this paper is organized as follow: Section II provides a brief background coverage of distance estimation using mobile phones and methods for step detection. Section III introduces our FSM-based method for step detection and our SVM classifier. Details about the experiments and their results are provided in Section IV. Finally Section V concludes the paper.

II. BACKGROUND

Dead reckoning [6] is a relative navigation technique through which the new location of a user is estimated with the help of the start location, the distance traveled, and direction of motion.

$$X_{k+1} = X_k + S * \cos(\theta), Y_{k+1} = Y_k + S * \sin(\theta) \quad (1)$$

Where X_k , and Y_k identify the user's location at time index k , S is the displacement, and θ represents the direction of motion. Typically the step length S is estimated with the help of accelerometers and the direction θ is estimated with help of magnetometers and gyroscopes. In order to efficiently apply the dead reckoning technique we need: (1) an accurate detection of the user's displacement and (2) a precise estimation of the heading direction. In this paper we focus on the first problem using commodity mobile phones and leave the heading estimation problem to a future paper.

In the balance of this section, we briefly describe the stat-of-art techniques for estimating the user's displacement which we compare against in Section IV.

A. Displacement Estimation by Integration

Displacement can be obtained from the acceleration signal by double integration with respect to time. However, due to the presence of noise in the accelerometer output, error accumulates rapidly with time. Another source of error is the presence of a component of acceleration due to the gravity of the earth when the phone has an arbitrary orientation. These factors lead to errors in displacement that will grow cubically with time and can reach 100 meters after one minute of operation with accurate foot mounted accelerometers [9]. This becomes even worse with the low cost and low quality phone sensors where our experiments show that the displacement error can reach 120 meters in one minute.

To overcome this error accumulation, previous phone-based techniques, e.g. [4], periodically synchronize with the GPS to reset the error to zero. However, GPS does not work indoors. In addition, since the gyroscope is not widely used in phones yet, it is hard to distinguish between the acceleration caused by linear movement and the acceleration caused by rotating the phone. Therefore, whenever the phone

rotates, its frame of reference gets affected and this presents a challenge for distance estimation from the acceleration values. Another approach to handle the error accumulation is the Zero Velocity Update (ZUPT) method where the velocity is set to Zero when the user's foot is detected to be stationary. However this method can only be used when it is easy to detect the stationary periods between footsteps, e.g. for foot mounted accelerometers [8].

B. Displacement Estimation by Step Detection

Another method to avoid the accumulation of error is to estimate displacement based on estimating the user's steps and multiplying the step count by a *constant* step size to estimate the displacement. We present here two of the state-of-the-art step detection techniques: the local variance method and the zero crossing method.

1) *Local variance threshold method*: The local variance threshold method [10] is based on filtering the magnitude of acceleration followed by applying a threshold on the variance of acceleration over a sliding window. However, its current implementation depends on high accuracy foot-mounted accelerometers, which differ significantly from phone-embedded sensors. We quantify its performance when applied to phone sensors in Section IV.

2) *Zero crossing method*: Another method for step detection based on acceleration values is the zero crossing method discussed in [11]. This method first computes the magnitude of the acceleration signal. The step boundaries are defined by the positive-going zero crossing of a low-pass filtered version of the magnitude of acceleration signal. Again, this method have been applied to foot-mounted sensors and we quantify its performance when applied to phone sensors in Section IV.

C. Discussion

Step detection based methods have either been applied to foot-mounted sensors or assumed a fixed phone orientation; both are far from the typical case for a phone-based inertial navigation system. In addition, previous work in dead reckoning using mobile phones, e.g. [7], [8], considered the stride length of each step to be constant. Our proposed work relaxes these three assumptions. We compare against these different techniques in Section IV.

III. SYSTEM DESIGN

Figure 1 shows the system architecture. Our architecture consists of two main modules: the step detection and step length estimation modules. The **Step Detection Module** is responsible for determining the step boundaries based on the raw sensor values. The **Stride Length Estimation Module** is responsible for estimating the step length based on the user gait. It contains three sub modules: (1) the **Features Generation Module** which processes the acceleration signal within the estimated step to generate features for the gait

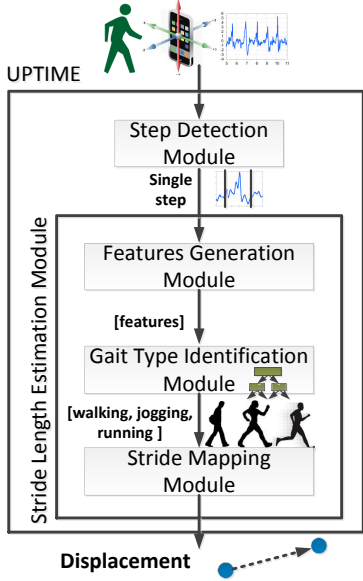


Figure 1. UPTIME system architecture.

type detection, (2) the **Gait Type Identification Module** identifies the gait type using a SVM classifier, and (3) the **Stride Mapping Module** gives an estimate for the stride length based on the estimated gait. In the balance of this section, we give the details of the two modules.

A. First Module: Step Detection

Most of modern mobile phones have a built-in 3-axis accelerometer sensor to detect the orientation change of the phone. These sensors measure the force applied on the phone. The measured values represent a combination of the applied acceleration on the phone due to motion and the force of earth gravity. The coordinate-system is defined relative to the screen of the phone in its default orientation. This introduces the challenge of dealing with the effect of gravity that may be present in the three axes of acceleration with components depending on the orientation and tilt of the phone. In particular, the user's step typically rises then falls continuously perpendicular to the direction of motion. Since the user may have the phone in any arbitrary orientation, including in pocket, and the tilt and orientation of the phone may change *during the interval of a step*, it is hard to estimate the horizontal user's acceleration based on the raw acceleration signal. This highlights the need for a step detection method that is independent from the phone orientation.

Based on our experiments, we noticed that the effect of walking on the magnitude of the 3D acceleration vector is independent from the phone orientation and tilt. Therefore, we design our system based on the magnitude of acceleration. Figure 2 shows a typical example of the magnitude of acceleration for a phone held in hand and in pocket.

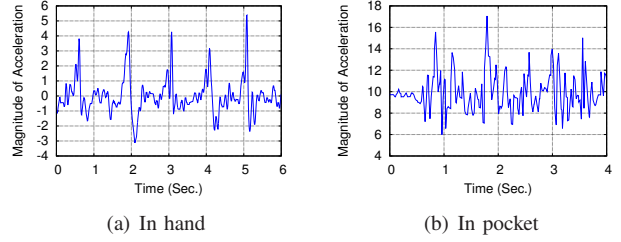


Figure 2. Magnitude of the 3D acceleration vector during walking for five steps with the phone in hand and in pocket.

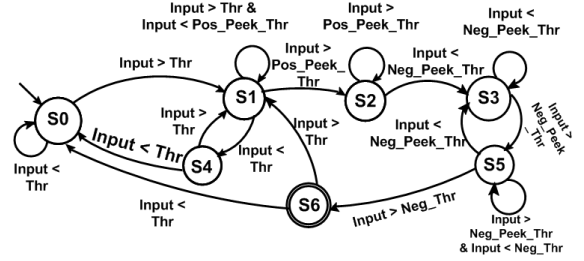


Figure 3. The FSM for step detection using the magnitude of acceleration as a feature.

Table I
LIST OF THE THRESHOLDS USED IN THE FSM-BASED STEP DETECTION ALGORITHM.

Name	Thr	Pos_Peek_Thr	Neg_Peek_Thr	Neg_Thr
Value	0.6	1.8	-1	-0.6

The figure shows that the noise in the in-pocket case is higher than the in-hand case due to the phone shakes inside the pocket. However, both cases show a similar pattern for the magnitude of acceleration, highlighting its promise as a feature for step detection ².

From Figure 2, we notice that the magnitude of the acceleration signal goes to a positive peak value followed by a negative peak value during each step. Based on this observation, we designed and implemented a FSM-based step detection algorithm. The FSM is shown in Figure 3. The input signal for the FSM is the magnitude of the 3D acceleration vector.

There are two main states: S_0 , representing the case when the user is not walking and S_1 , representing the case when the user has possibly started a step. Another two accessory states are used: S_2 and S_3 indicating that a positive or negative peek has been reached respectively. Two more states are used to tolerate the noise: S_4 and S_5 . S_6 represents the terminal state. A number of thresholds are applied to the acceleration magnitude to decide to move from one state to another. These thresholds are found to be stable and their values are listed in Table I.

Starting from state S_0 , the following transitions have to

²The number of steps in both cases were detected correctly using our FSM technique.

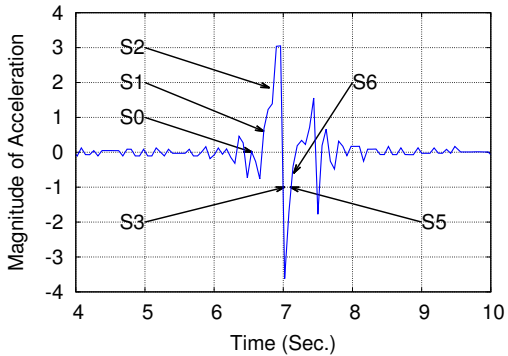


Figure 4. An example of the state transitions during the detection of one step.

Table II
MEAN OF STEP SIZE BY WALKING FOR 100 STEPS UNDER DIFFERENT GAIT TYPES. A CONSTANT STEP SIZE ASSUMPTION CAN LEAD TO SIGNIFICANT ERROR IN DISPLACEMENT ESTIMATION.

Gait Type	Average Step	Percen. difference relative to walking
Walking	0.74m	0%
Jogging	1.01m	36%
Running	1.70m	130%

occur to announce a new step: the acceleration magnitude exceeds the threshold (Thr) leading to a transition from state S_0 to state S_1 . The signal has to exceed a positive threshold (Pos_Peek_Thr) and then go back to exceed a negative threshold (Neg_Peek_Thr) leading to a transition to state S_2 and then S_3 . The signal has to go back to zero through state S_5 (exceeding the Neg_Peek_Thr threshold). Finally, the end of the step is marked by the transition from state S_5 to state S_6 , detected by going below another threshold (Neg_Thr). Figure 4 shows an example for the state transitions that happen during detecting one step.

The advantages of this FSM approach are: (1) It does not require any preprocessing or filtering operations on the acceleration signal. Therefore, it is suitable for implementation on the resource-limited mobile phones. (2) It works regardless from the orientation and placement of the mobile phone.

We evaluate the accuracy of the technique and compare it to other state-of-the-art step detection algorithms in Section IV.

B. Second Module: Stride Length Estimation

Previous work in pedestrian dead reckoning, e.g. [7], [8], assume that the average step size for the same person is constant. As shown from our results in Table II, the stride length changes significantly for the same person when the gait type changes (up to 130% in our experiment). Therefore, UPTIME is based on using a variable step size, as compared to a constant step size as in previous techniques.

Our approach is based on training a classifier to differenti-

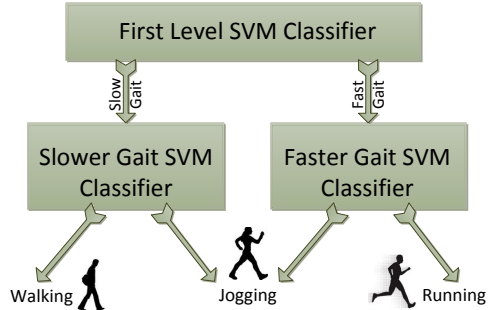


Figure 5. UPTIME SVM multi-class classifier.

ate between the three different gait types: walking, jogging, and running. We use the following features:

- *The duration of the step*: the longer the duration the slower the user's gait.
- *The variance of acceleration signal*: The higher the variance, the faster the gait.
- *Peak value of acceleration*: Faster gaits have higher acceleration peak.
- *The difference between the maximum and minimum acceleration during a step*: The higher the difference, the faster the gait.
- *Root-Mean-Square value of acceleration*: The higher the root mean square (RMS) value, the faster the gait.
- *The result of multiplying the root mean square value with the step duration*: The RMS of acceleration indicates the intensity of motion which is correlated to the walking speed. This metric, multiplies the RMS by the step duration as an indication of the distance within the step.

These features are extracted by the **Features Extraction Module** which then feeds them to the **Gait Type identification Module** that uses a multi-class hierarchical Support Vector Machine (SVM) classifier (as shown in Figure 5). The first level classifier differentiates between slower and faster gaits. The second level classifiers do a more fine grained classification to identify the specific gait: walking, jogging, or running.

Once the gait type is identified, the **Stride Mapping Module** returns an estimate for the displacement during this step. Different techniques can be used: we use a simple table lookup, based on Table II, in this paper due to space constraints.

IV. EXPERIMENTAL RESULTS

In this section, we evaluate UPTIME in different testbeds and compare it to the other systems described in Section II. We start by describing the system setup followed by the evaluation of the step boundary detection module, the step size estimation, and the combined tracking performance. For space constraints, we only give the details for the outdoor testbed, which has the higher error due to the more flexibility

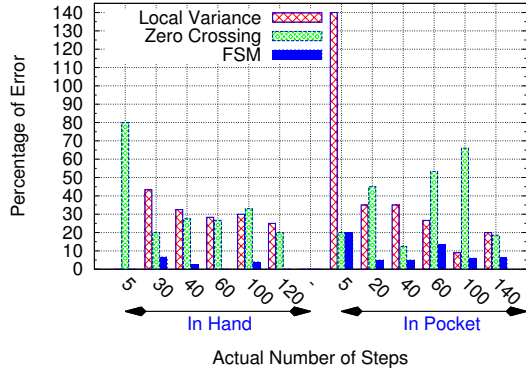


Figure 6. Relative error for the three step detection techniques for different phone orientations and step sizes.

Table III

AVERAGE ERROR IN ESTIMATING THE NUMBER OF STEPS USING THE LOCAL VARIANCE [10], ZERO CROSSING [11] AND OUR FSM-BASED METHODS.

Technique	Local Variance [10]	Zero Crossing [11]	FSM
In hand	27.18%	30.19%	2.66%
In pocket	44.27%	34.07%	9.29%
Overall	35.08%	31.98%	5.72%

in motion, and only the tracking error for the indoor testbed. Therefore, the reported results are conservative.

A. Experiment Setup

We implemented UPTIME on Samsung Galaxy S and Vodafone 845 Android phones. In our experiments, different users carrying phones walk for a number of trips with different lengths, i.e. step sizes. Some trips are made indoors, while others are made in the open area around our campus. During some trips, the user is carrying the phone in hand, while in others, the phone is put inside the users' pocket *to study the effect of arbitrary phone orientation*.

B. Step Boundary Estimation

Figure 6 shows the result of applying the three step detection algorithms on measured acceleration values when the phone is kept in hand and in pocket. Table III summarizes the results. The results indicate that our FSM-based algorithms significantly outperforms the other techniques (at least six times better) with an average error of 5.72%. Since other techniques are designed to work with foot-mounted sensors, their accuracy significantly degrades when applied to the phone sensors. Comparing the in-hand to in-pocket performance, all techniques perform better in the in-hand case. This is due to the more noise introduced when the phone is placed in pocket.

C. Step length Estimation

Table IV shows the confusion matrix of the SVM classifier. The table shows that the overall classification accuracy

Table IV
CONFUSION MATRIX OF CLASSIFYING THE GAIT TYPE.

Mode	Walking	Jogging	Running
Walking	479	1	0
Jogging	18	572	0
Running	5	5	206

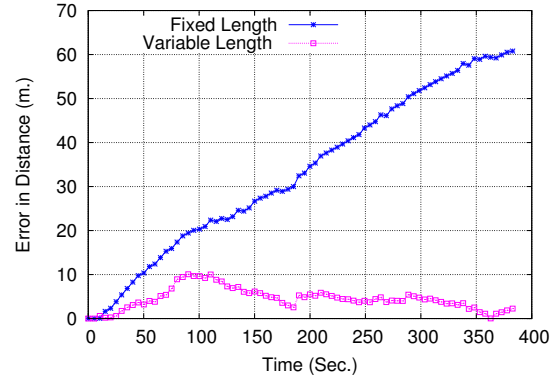


Figure 7. Comparison between the error of distance estimated by employing a fixed stride length algorithm and our variable stride length based on the different gait types.

is 97.74%.

Figure 7 compares the accuracy of using a constant step length, as in the case of the current approaches, to the accuracy of using a variable step size in UPTIME for one trip. The trip involves walking for 470 meters over a period of 6.3 minutes around our campus with a phone held in hand using different gaits. The GPS is used as a ground truth. The figure shows that using a constant step length that does not fit the actual user gait leads to accumulation of error. On the other hand, UPTIME error is bounded due to its variable step length approach. Note that UPTIME error varies with time due to the variation of the user's actual step length from the per gait average and the classifier limited error.

D. Tracking Accuracy

In this section, we present the combined tracking accuracy when applying both modules together for an indoor and an outdoor testbed. Figure 8 shows the estimated trace of the user's motion for a distance of 623 meters around a residential compound in our campus over a period of 11 minutes. The dashed black line shows the ground truth measured by the GPS and the blue pins represent the estimated trace of motion by UPTIME. The error in this testbed was only 33 meters corresponding to a tracking error of 6.9%.

Figure 9 shows the estimated user trace inside a building with dimensions 48m \times 45m using UPTIME. The dashed red line shows the ground truth of motion (length = 95m) and the blue solid line shows the estimated trace. The distance error in this testbed was 4m corresponding to a tracking error



Figure 8. Trace of user's motion estimated by dead reckoning

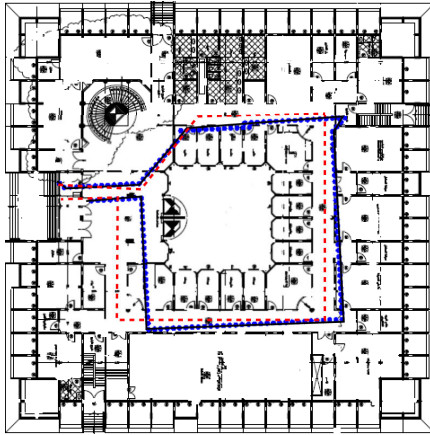


Figure 9. Trace of user's motion inside a building estimated by dead reckoning

of 5.9%. This highlights that the indoor accuracy is higher than the outdoor accuracy which is due to the flexibility in motion in outdoor environments.

V. CONCLUSION

In this paper, we presented UPTIME as a mobile phone-based system for ubiquitous pedestrian tracking that works in both outdoor and indoor environments. The system combines a novel FSM approach for step boundary estimation with a SVM classifier for estimating the variable step size based on the user gait. We presented the details of the FSM and the orientation independent features that allows our system to provide high accuracy of tracking.

To evaluate our system, we implemented it on Android-based phones and compared it to the state-of-the-art systems. Our results show that our FSM-based step detection algorithm can achieve an accurate estimation with less than 5.72% error for arbitrary phone orientations. In addition, our SVM classifier achieves 97.74% accuracy with most of the error to adjacent classes. Combining both modules together, UPTIME provides a high tracking accuracy with less than 6.9% error in distance estimation for both indoor and outdoor environments.

Currently, we are expanding our system in different direction including enhancing accuracy by error resetting by synchronizing with the environment and other users, estimating accurate user direction, performing map matching, among others.

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