

uDirect: A Novel Approach for Pervasive Observation of User Direction with Mobile Phones

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Abstract—In this paper we present the uDirect algorithm as a novel approach for mobile phone centric observation of a user's facing direction, through which the device and user orientations relative to earth coordinate are estimated. While the device orientation estimation is based on accelerometer and magnetometer measurements in standing mode, the unique behavior of measured acceleration during stance phase of a human's walking cycle is used for detecting user direction. Furthermore, the algorithm is independent of initial orientation of the device which gives the user higher space of freedom for long term observations. As the algorithm only relies on embedded accelerometer and magnetometer sensors of the mobile phone, it is not susceptible to shadowing effect as GPS. In addition, by performing independent estimations during each step of walking the model is robust to error accumulation. Evaluating the algorithm with 180 data samples from 10 participants has empirically confirmed the assumptions of our analytical model about the unique characteristics of the human stance phase for direction estimation. Moreover, our initial inspection has shown a system based on our algorithm outperforms conventional use of GPS and PCA analysis based techniques for walking distances more than 2 steps.

Keywords : *direction detection, walking locomotion, acceleration, pervasive computing, Mobilephone,*

I. INTRODUCTION:

Finding a user's facing direction has been for long a goal for researchers in a variety of research fields from localization in wireless networks and robotics areas to recent social and behavioral analysis with wearable computing technologies and smart environments. Past systems for the detection of users' directionality in constraint locations and short periods of time made typically use of ambient [1-3] and Body Sensor Networks (BSN) [4-6].

However, due to the dependency of ambient sensors on infrastructures and the intrusiveness of the BSN (which despite of the advances in miniaturization of sensors is still the main obstacle for their application for long periods of time) there is still a remaining need for an observer to collect long term and ubiquitous information about user. Consequently, the real world applications of these observations techniques are confined to limited surveillance e.g. [7] and affective computing (e.g. [2] and [8]) when using ambient sensors and in case of wearable sensors to analyzing social behavior of a group of participants during a

study (e.g. [4] and [5]), pilot demonstrations of dead reckoning technique (e.g. [9] and [10]) and healthcare studies [11].

New advances in computing, storage and wireless technology along the recent introduction of Micro Electro Mechanical System (MEMS) based sensors into mobile phones, has opened the door to a new world of application possibilities. The indispensable role of the mobile phones in today's life makes mobile phone centric sensing systems ideal candidates for serving as ubiquitous observers. The available mobile network infrastructure can also facilitate the large scale data collection and modeling for variety of applications.

In this work we present uDirect as a novel approach for pervasive observation of user's facing direction using mobile phones. For its estimation, uDirect makes use of built-in accelerometer and magnetometer sensors readily available in many mobile phones. It assumes that the mobile phone is carried in the trouser pockets of a user and exploits unique acceleration patterns of human walking locomotion. As everyday life usage of mobile phones demands, uDirect estimations are independent of the mobile phone orientation. Furthermore uDirect does not require any previous training samples. During evaluation of a proof-of-concept implementation with 10 participants on an Android based smart phone we were able to verify our underlying theoretic models and show that our algorithm performs more accurate than existing GPS based methods or PCA based techniques exploiting inertial sensors, while providing several advantages compared to those. In summary we make the following contributions:

We present uDirect an approach to determine a user's facing direction with a mobile phone, regardless of the mobile phone's orientation.

For this we propose a novel method for auto calibration of the mobile phone orientation based accelerometer and magnetometer sensors of the phone. Auto-calibration is achieved by determining the rotation quaternion between the sensed earth co-ordinate system and the actual co-ordinate system of the mobile phone. The underlying mathematical model using the quaternion presentation further simplifies computation of the rotation compared to a vector based approach.

We further propose a novel approach for determining a user's forward direction based on accelerometers, exploiting the physiological walking behavior of a human. By analyzing the acceleration pattern of the thigh movement during walking

locomotion, we are able to identify the optimum moment where the captured acceleration signal mainly consist of the forward direction, minimizing the noise of unwanted side components.

We report on the evaluation of uDirect based on 180 data samples collected from 10 participants validating our underlying theoretical models and comparing the performance to existing approaches.

The remaining paper will first introduce the related works in Section II, before describing an overview of the uDirect algorithm in section III. In section IV the underlying theories and mathematical model are discussed. Section V reports on the experimental evaluation of an implemented prototype. Concluding remarks are provided in Section VI

II. RELATED WORK

The wearable sensors community has produced a variety of direction detection techniques which can be implemented with minor modifications on mobile devices. A typical solution for detecting user direction can be frequent logging of the user's absolute location. However, providing the required absolute location depends on the availability of infrastructure such as ultra wide band, GSM and Wi-Fi transceivers. Furthermore the performance of such systems may be adversely affected by shadowing and interference in the environment. Another approach based on wearable cameras and the subsequent analysis of the taken pictures has been successfully implemented in [12] and [13]. But these techniques require significant computational and storage resources.

Inertial sensors such as accelerometers and gyroscopes have been also used for direction estimation. For example, in [10] a technique is proposed that performs Principal Component Analysis (PCA) over horizontal acceleration components during walking locomotion. In this approach vertical and horizontal components are distinguished through Kalman filtering of measured acceleration and angular velocity. The direction of the first principal component is then used as an estimation of user facing directionality. However, according to [14], the processing of gyroscopes signals typically requires a large number of sine/cosine and coordinates transform operations, and puts a heavy computational burden on the processor, which makes it less suited for pervasive computing environments. The respective authors concluded to avoid the use of gyros if the detection could be carried out only by accelerometers. Recently Kunze et.al [15] have developed a direction estimation technique based on mobile phone accelerometer readings when the device is placed in user trousers pocket. Similarly to [10], PCA analysis is applied over horizontal acceleration components during walking locomotion. Horizontal and vertical components are distinguished by detecting gravity direction from acceleration sample in stationary mode. We have used this direction estimation technique that has been successfully implemented on a mobile phone for comparison with our proposed model.

Direction detection with magnetometer as an accurate and computational efficient approach, has also attracted many researchers (e.g. [9][16][17][19]). These approaches require a pre-defined device orientation relative to user, which is typically

achieved by fixing the device position on user body. In order to compensate for magnetic noise in the environment, simple offset estimation and filtering techniques (e.g. [12], [20]) are utilized accuracies suitable enough for many applications.

However carrying a device (in our case mobile phone) with a fixed position and orientation for a long period of time is clearly intrusive and not practical for long-term observations. In this study, we introduced the uDirect algorithm which uses magnetometer and accelerometer embedded in mobile phone for pervasive observation of user direction. Despite providing high accuracy, uDirect algorithm detects the user direction without any previous knowledge about device orientation relative to users.

III. UDIRECT ALGORITHM DESIGN

The uDirect algorithm exploits the acceleration pattern measured during walking locomotion to perceive the user facing direction. In this section we provide an overview of the algorithm by briefly introducing its key technical components.

The goal of the work is to find the relative orientation of each user with respect to a global reference coordinate system. In this regard we consider the earth coordinate as our reference coordinate system, which is aligned through North, East and opposite direction of gravity and through the algorithm process we calculate the orientation of user coordinate in earth coordinate. The user coordinate system is depicted in fig.1 with F, S and V axis, where F stands for forward direction, V is vertical direction and S is the side direction along the cross product of V and F. Any rotation of body segments during movement can be expressed as a rotation around one of these axes. For example, sagittal rotation would be around S and transverse rotation would be around V. Body rotational planes including sagittal, coronal and transverse planes are shown in fig.1.

The uDirect algorithm performs the estimation of the user facing direction in two main steps, as depicted in the flow chart in fig.2. The algorithm first starts with determining the device orientation relative to earth coordinate when the user is in standing mode using mobile phone embedded accelerometer and magnetometer. In this stage, the device calibrates its measurements by transferring them into earth coordinate system.

In the second step, the behavior of acceleration generated during walking is used to obtain the relative orientation of the user to the earth coordinate system. During this stage, the component which is aligned towards the user forward direction (F) is separated from the sampled acceleration information and using the calibration information from the first stage enables us to calculate the user direction within in earth coordinate system. Note that, here we have implicitly assumed that people are normally moving forward. This seems to be a valid assumption for most cases, since our field of view is in the forward direction.

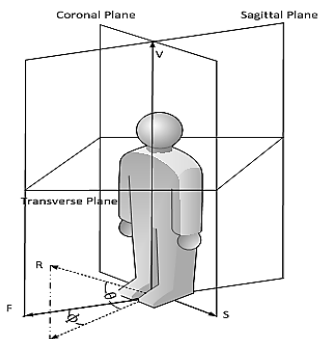


Figure 1. User coordinates and body rotation planes

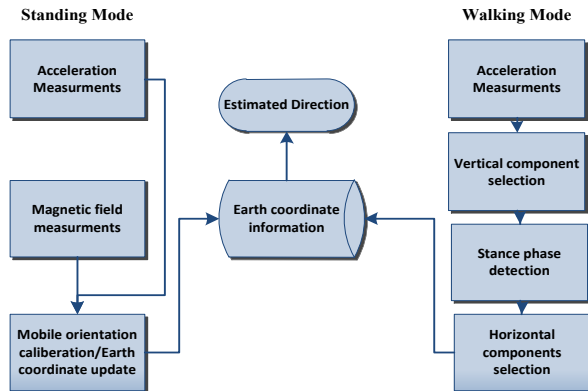


Figure 2. Flow chart of uDirect algorithm, the calibration is performed in stationary mode and direction is estimated during walking mode.

Although the processes in both steps are independent from device orientation, the analysis in the second step of algorithm requires the device position to be known. That is because of high dependency between measured acceleration during different activities and measuring position on body (for extensive discussions refer to [19]).

In the currently implemented version of the uDirect, we assume as in [15] that the mobile phone is placed in the trouser pocket of the user. Several studies have emphasized on the trouser pocket as one of the primary positions of mobile phones in users daily life (e.g. [21]). For example, a study in [22] has shown that in average 60 percent of male users put their mobile phones in their trousers pocket. In contrast to other common positions of the device including chest pocket or bag, trousers pocket are the closest to Centre of Gravity (COG) of body, where, the applied force in its proximity is claimed to be almost deterministic and undisturbed by individual's physical characteristics. Selecting trouser pocket or equivalently the Femur (as the related body segment), we also simplify the analysis of acceleration by limiting the device movements during walking in the sagittal and transverse plane.

IV. METHODOLOGY

Following the sequence of operations of the proposed algorithm, this section first introduces the technique that is used

for the calibration of the device orientation, before presenting the proposed analytical model for device acceleration during walking locomotion. By using empirical data from body movement, we show in the last section how measured acceleration at specific phases of the walking cycle can provide accurate estimations of user direction.

A. Calibrating the mobile device orientation

Detecting mobile orientation with respect to the earth coordinate system is based on two main features, namely gravity acceleration and the earth magnetic field. By observing the gravity acceleration and geomagnetic field in any coordinate system we are able calculate the vertical (-g) and north axis of the earth coordinate system in the observation coordinate system.

In the case of gravity a similar approach as presented in [23] is adopted where the average of signals is taken when the phone is in stationary mode (when the user is standing). Here, stationary mode is identified as a period of time when the variance of the samples over a sampling window is approximately zero. By averaging over a sampling window the measured acceleration as gravity (g) and magnetic field samples (M) in stationary mode, the earth coordination in mobile phone can be calculated as follow:

Considering the inverse of gravity vector (-g) as Z, we can compensate the dip angle of measured magnetic field (M) by projecting it into the new XY plane, perpendicular to Z. Therefore, North direction (X) is calculated as

$$X = Z \wedge M \wedge Z, \quad (1)$$

and Y which stands for the East direction is calculated as cross product of the X and Z.

$$Y = X \wedge Z \quad (2)$$

Now X, Y and Z are aligned to the earth static coordinate system and are corresponding to North, East and the inverse of the gravity direction. Having determined the earth coordination components with respect to the mobile device coordinate system, we can now calculate the rotation matrix that transforms these two coordinate systems into each other.

The most common method of representing the rotation difference is by calculating the Euler angles and corresponding rotation matrix. However, an alternative method is to use the quaternion representation invented by Hamilton in 1866 [24]. Because of the more compact encoding, the use of quaternions has computational advantages compared to singular representation (like Euler equations). While the singular representation of these transformations requires nine real numbers (as 3×3) and operations, quaternion representations require only four.

Quaternions are a single example of more general class of hyper-complex numbers and belong to non-commutative division algebra. Analogous to complex numbers, a quaternion (H) can also be written as a linear combination of real and imaginary

parts by $H = w + ia + jb + ck$ while $i^2 = j^2 = k^2 = -1$. Using this construction the composition of three rotations that forms a movement in 3D space, can be written as a simple rotation around one axis as follow:

$$R(\hat{V}) = Q\hat{V}Q^* \quad (3)$$

Here R is rotation function and Q is a quaternion that represents the rotation of 3D vector \hat{V} by angle of 2θ around vector \hat{u} which can be calculated as

$$Q = \cos\theta + \hat{u}\sin\theta \quad (4)$$

As previously pointed out in order to map the sensed acceleration into the earth's coordinate system we require the rotation component that transforms the mobile device co-ordinate system (x, y, z) to the earth coordinate (X, Y, Z). In the following lines, we compute this rotation quaternion in three steps: First, the quaternion that rotates z to Z,

$$Q_1 = \cos(\theta/2) + \hat{u}\sin(\theta/2) \quad (5)$$

$$\theta = 2(Z.z)/\|z\|\|Z\| \quad (6)$$

$$\hat{u} = |Z \wedge z| \quad (7)$$

Secondly, we calculate Q_2 , the quaternion that rotates the projection of y on the transverse plane, into the direction of North(X). It can be represented with same notation as Q_1 in (5) while u is substituted with Z and θ with θ' . Where

$$\theta' = 2(X.(Z \wedge y \wedge Z)) / (\|X\|\|Z \wedge y \wedge Z\|) \quad (8)$$

Combining Q_1 and Q_2 to have the resultant rotation quaternion, with following the quaternions multiplication rule, the succeeding result can be obtained:

$$R = Q_1Q_2 = \cos(\theta/2)\cos(\theta'/2) + \hat{Z}\cos(\theta/2)\sin(\theta'/2) + \hat{u}\cos(\theta'/2)\sin(\theta/2) + \hat{u} \wedge \hat{Z} \quad (9)$$

Once R has been determined, the measured values from an arbitrary orientation of the device can be read in the static earth coordinate system. This calibration process will be later used to transform the measured values for user direction into the earth coordination system to provide the absolute direction of a user.

Re-calculation of the rotation is only required when the user changes the position or orientation of the phone. It is worth noting that the earth and user coordinate systems share the same vertical axis, as shown in fig.1. As will be discussed in the next

section, this fact helps us to confine our acceleration pattern analysis to only components in the transverse (horizontal) plane.

B. Calculating the dynamic model of device acceleration during walking locomotion

Considering the body segments of a human as a rigid body for formulating their dynamics has been long used by researchers [25]. In our study, the goal of this modeling is to relate the measurements of accelerometers with a user's movement direction. Assuming based on the previous section that the measurement coordinate (mobile) is calibrated with a global reference (earth) we will be able to estimate the user direction in earth coordinate system. However, as was previously stated, in reality the vertical direction is the only information that is available about a user's orientation which is assumed to be in parallel with gravity.

Now, considering the fact that by detecting the vertical direction and deducing it from total measured acceleration we are able calculate the resultant of horizontal components of user coordinate, we have proposed the following algorithm to overcome these limitations and to achieve our goal.

1- Assuming that the user coordinate system is known, we calculate the device measurements based on its deviations (during walking locomotion) from user's coordinate system. Here, the modeled values would show the device measurements as effect of user translational and body segment rotational movements in an arbitrary orientation of device.

2- The measured components are transferred into user coordinate system. From now, we can analyze the behavior of the measured components in user coordinates.

3- We focus on the behavior of the horizontal components of measured accelerations to find the characteristics in which the resultant acceleration is dominated by forward (F) components.

In order to develop the mentioned algorithm, we base our formulation onto the same assumption as [26] and consider the hip joint as ball joint which permits Femur rotation in all directions. However, during walking, the major Femur rotations only take place in the sagittal (around S) and transverse plane (around V).

In order to explain the dynamics of movement the following coordinate systems are introduced and depicted fig.3:

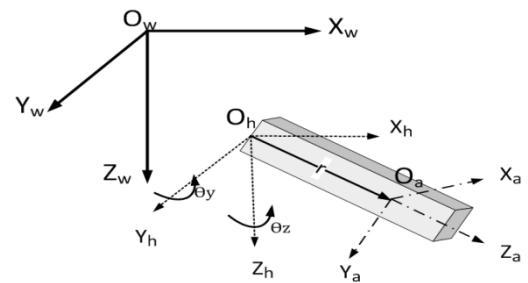


Figure 3. Coordination systems and rotation directions, Og stands for center of global coordination, Oh center of local coordination (hip joint) and Oa for center of accelerometer coordination system. Θ_z rotation around Z_g and Θ_y rotation around Y_g

$O_w-X_wY_wZ_w$ is the world (global) coordinate system where Z is pointing towards earth and the X is towards a user's forward movement, $O_h-X_hY_hZ_h$ is the local coordinate system at the hip joint which is parallel to world coordinate and finally, $O_a-X_aY_aZ_a$ is the accelerometer coordinate system which is placed on the rigid body (Femur). For simplicity, we consider the accelerometer coordinate system to be parallel with other coordinate systems at time 0 when the longer axis of the femur is aligned along gravity vector (or Z_w).

From the relative acceleration principle, the acceleration that is measured in the O_a after t seconds from the start of movement can be expressed as follow:

$$A_{oa}(t) = A_{ah}(t) + A_{hw}(t) \quad (10)$$

Where A_{oa} is the measured acceleration at O_a , A_{ah} is the relative acceleration in O_a when the rigid body rotates around O_h and A_{hw} is the acceleration of O_h relative to O_w . Since the distance between O_a and O_h , is constant the relative acceleration between O_a and O_h can be expressed as:

$$A_{ah} = \dot{\omega} \wedge r + \omega \wedge (\omega \wedge r) = \begin{bmatrix} r\dot{\theta}_y - r\dot{\theta}_z \\ r\ddot{\theta}_z \\ r\ddot{\theta}_y \end{bmatrix} \quad (11)$$

The term $\dot{\omega} \wedge r$ is produced by the angular acceleration of the measuring coordinate system and the other term represents the centripetal acceleration.

The relative acceleration of the O_a and O_w consist of the gravity and translational acceleration.

To obtain the resulted acceleration based on rotated coordinate of device we have:

$$A_{hw} = R_{\theta_y}(t)R_{\theta_z}(t)(G + A_{Oh}(t)) \quad (12)$$

Here R_{θ_y} and R_{θ_z} are the Euler rotation matrices around Y_w and Z_w (sagittal and transverse rotations) at time t by the angles of $\theta_y(t)$ and $\theta_z(t)$ respectively. A_{oh} and G are also translational acceleration and acceleration of gravity in the global coordination system $O_w-X_wY_wZ_w$.

With the same methodology as mentioned in the previous section the combination of these two rotations can be more computationally efficiently represented by one quaternion. Here the resultant quaternion is described as:

$$R(t) = ((\cos(\theta_z(t)/2)\cos(\theta_y(t)/2), \sin(\theta_z(t)/2)\sin(\theta_y(t)/2), \cos(\theta_z(t)/2)\sin(\theta_y(t)/2), \sin(\theta_z(t)/2)\cos(\theta_y(t)/2)) \quad (13)$$

Therefore the final equation for measured acceleration is

$$A_{oa}(t) = A_{ah}(t) + R(t)(G + A_{Oh}(t))R(t)^* \quad (14)$$

Inserting values form (13) and (15) to (16) and considering A is equal to $G + A_{oh}$ we obtain:

$$A_{oa}(t) = \begin{bmatrix} \cos\theta_z(t)\cos\theta_y(t)A_x + \sin\theta_z(t)A_y - \cos\theta_z(t)\sin\theta_y(t)A_z + r\dot{\theta}_y - r\dot{\theta}_z \\ -\sin\theta_z(t)\cos\theta_y(t)A_x + \cos\theta_y(t)A_z + \sin\theta_y(t)\sin\theta_z(t)A_z + r\ddot{\theta}_z \\ \sin\theta_y(t)A_x + \cos\theta_y(t)A_z + r\ddot{\theta}_y \end{bmatrix} \quad (15)$$

Equation (15) represents the measured acceleration in device coordinate system. Let's recall that our goal of modeling was to relate the device measurements with user direction. One solution is to use rotational information ($R(t)$) to transform the measured acceleration in (15) into the directions of user's coordinate axis. But in reality, a user's mobile phone can be carried with any arbitrary orientation relative to user coordinate system and our knowledge about user coordinate is limited to its vertical direction (which is in parallel with gravity). Therefore, we can only determine the sagittal rotation, and transverse rotation remains unknown. 1

Our solution is to find the moments during walking locomotion in which the acceleration along the forward direction dominates the measured acceleration in transverse plane. More precisely, while from the sagittal rotation information the transverse plane of user coordinate is known, the user direction in the transverse plane can be determined when the main acceleration components belong to the forward acceleration (F) or equivalently the side acceleration components (S) is in its minimum.

To analyze the measured acceleration behavior in the transverse plane, we assume that the device rotation compared to the user's coordinate system is known. We can transfer the measured acceleration into user coordinate. $A'_{oa}(t)$ as the measured acceleration in user coordinate can be calculated as :

$$A'_{oa}(t) = R^*(t)(A_{oa}(t) + R(t)(G + A_{Oh}(t))R(t)^*)R(t) \quad (16)$$

Substituting appropriate values from (13) and (15) into (16) the, resultant acceleration vector can be finally expressed as:

$$A'_{oa}(t) = \begin{bmatrix} \cos\theta_y(t)\cos\theta_z(t)A_{xx} - \cos\theta_y(t)\sin\theta_z(t)A_{xy} + \sin\theta_y(t)A_{xz} \\ \sin\theta_z(t)A_x - \cos\theta_z(t)A_y \\ -\sin\theta_y(t)\cos\theta_z(t)A_{xx} + \sin\theta_y(t)\sin\theta_z(t)A_{xy} + \cos\theta_y(t)A_{xz} \end{bmatrix} + (A_{oh} + G) \quad (17)$$

Equation (17) shows the measured acceleration in the user's coordinate system. As was shown in fig.1 the Y and Z axis of the

1 Calculating the sagittal rotation or equivalently tilt angle is exactly the same as calculating the rotation required for aligning the Z axis of the device along gravity vector that has been discussed in previous part.

local and global coordinate system represent the axis of sagittal and transverse rotations which in user coordinate system, are called S (side) and V (vertical) respectively. From (17) it can also be inferred that compared to measurements in local coordinate (O_h), measuring acceleration in device (O_a) results in additions of rotational acceleration components along user coordinate axis.

Now, we need to find the situations in which the $A'_{oa}(t)$ along S (Aoay) is minimized. Adding rotational components from (11) to (17) the S acceleration is given by:

$$A_s = \sin(\theta_z(t))(r\dot{\theta}_y - r\dot{\theta}_z) - \cos(\theta_z(t))r\ddot{\theta}_z + (G + A_{oh})_y \quad (18)$$

Equation (20) shows that since gravity (G) has no component in x and y direction and the user is moving forward, in principal once transverse angular deviation ($\theta_z(t)$) and acceleration ($\ddot{\theta}_z(t)$) are near zero the magnitude of A_s is minimized. Through a comparison with empirical data in the next subsection, we have identified the moments during a walking cycle that meet these requirements.

C. Direction estimation

As shown in fig. 4 the walking cycle of a human can be divided into two main phases, a swing phase and a stance phase. The stance phase is usually referred to as the period of a walking cycle between each consequent heel strikes and toe off moments [25]. As will be shown later the transverse angular deviation and acceleration during stance phase meets the characteristics required for minimizing A_s in (18) and estimating user direction. Fig.5. shows the average femur transverse rotation for normal men based on empirical data from [27] and a polynomial curve that is fitted onto the empirical data. This polynomial will be used for as approximation in order to obtain the angular acceleration pattern. According to [27], the pattern of transverse rotation is preserved for different ages and heights and showing only variations in their magnitude. Furthermore, the pattern is continuously repeated and is almost the same for both feet [27].

Using Fourier transformation (FT) theory, this periodic pattern can be decomposed into a series of sine waves with different frequencies and phases. Since taking the double derivative of a sine wave only requires multiplication of it by minus of square of frequency regardless of its phase it is easily possible to construct the rotational acceleration pattern from the rotation pattern data. Constructing acceleration pattern from FT enables us to see the continuous form of acceleration during walking locomotion, which is not achievable by directly taking derivatives from our fitted polynomial.

We have reconstructed the transverse rotational pattern (θ_z) and its corresponding acceleration pattern ($\ddot{\theta}_z$) based on data taken from a polynomial² that is fitted on empirical data from

² A polynomial of order 8 has been taken while higher orders of polynomial didn't significantly improve the fitness of the curve.

[27]. The pattern of transverse acceleration during walking is depicted in fig.6.

From fig.5 and 6 we are able to distinguish the time instances in which the transverse deviation and acceleration is minimum. Referring to fig.6, transverse acceleration meets its minimum magnitude ($\ddot{\theta}_z = 0$) near the middle of the stance phase (35 % of walking cycle), when the primer foot (carrier of phone) is placed on the floor and the other foot is swinging. In addition, as is shown in fig.5 at this moment the device transverse orientation is approximately zero ($\theta_z = 0$). Another important characteristic of this moment is that the orientation of the device is close to the device orientation in standing mode.

Since the transverse plane was determined during the standing phase of a user, the mentioned characteristic implies that the gravity (G) components in transverse plane would be in its minimum ($G_x, G_y \cong 0$). Considering the fact that the user's translational acceleration during walking movement is towards the forward direction, we can now claim that the acceleration towards the side direction of the axis (A_s) from equation (18) would be minimum at this moment. It is worth noting that although we have shown that the A_s is minimum at the middle of stance phase, we have no proof that the forward acceleration is large enough to detect the forward direction reliably. However the empirical evaluation presented in the next section has confirmed that the magnitude of forward acceleration at stance phase is sufficient for providing accurate direction estimation.

To summarize, according to the characteristics of acceleration samples during walking locomotion we predict that the most appropriate moment for interpreting the measured acceleration in the transverse plane as user forward direction happens at the middle of the stance phase.

Now the only remaining issue is how to detect the stance phase. The toe off and heel strike moments as the start and end points of stance phase, can be accurately determined from the acceleration of Femur movement. These points are demonstrated in fig.6. Aminian et.al. have shown in [28] that during walking locomotion the local minima of acceleration samples in the vertical axis is corresponding to heel strike and global minima is corresponding to toe off moment. Developing a sensing application on a mobile phone and using a simple peak detection for detecting stance phase we have been able to evaluate our algorithms and assumptions. The results show that uDirect algorithm is able to detect the user direction with very high accuracy. The next section presents the evaluation process and results.

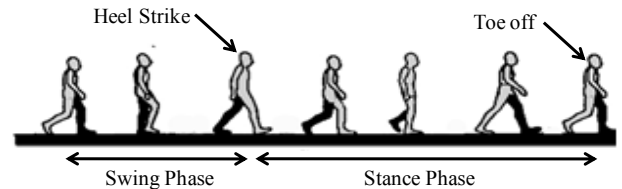


Figure 4. Walking locomotion, including two swing phases and one stance phase. The stance phase is started with heel strike and ended with toe off moments

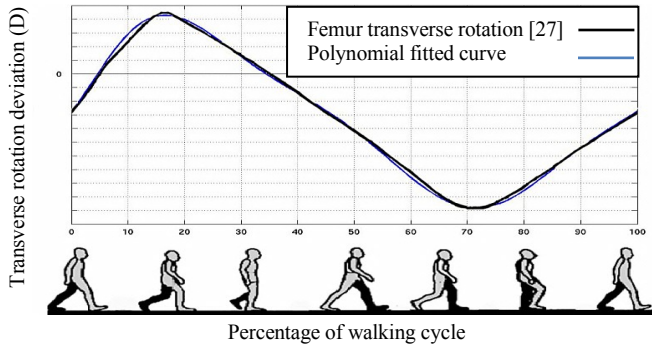


Figure 5. Transverse rotation of femur during walking locomotion. Average of data form different age groups form [27] and a polynomial curve fitted on average data are shown.

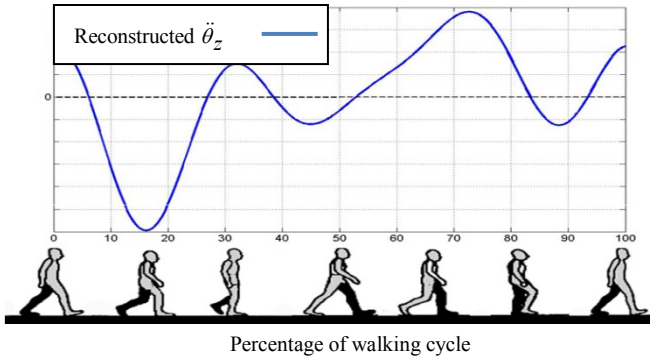


Figure 6. Transverse acceleration pattern, constructed form FFT components of transverse rotation, against walking cycle.

V. EVALUATION

The primary goal of our evaluation process is practically to verify the special characteristics of the stance phase in direction estimation that was previously derived with analytical modeling. In addition, we have initially examined the performance of an implemented prototype in comparison with current widely used approaches. During the next subsection the experiment procedure and results are presented.

A. Implementation

In order to evaluate the proposed algorithm we have developed a sensing application on an Android G1 dev phone.

The android G1 is equipped with a triaxial accelerometer combined with a Hall-effect geomagnetic sensor³ in three axes. The latter implements a Dynamic Offset Estimation (DOE) algorithm to automatically compensate the magnetic offset fluctuations thereby making it more resilient to magnetic field variation within device [29]. In addition, we have also mitigated the effect of high frequency ambient noise by averaging the measurements prior to the calibration of the device orientation.

Our application is able to simultaneously log accelerometer, magnetometer and GPS signals into a database with frequency of 25Hz for accelerometer and magnetometer and 1Hz for GPS. 10

³ Asahi Kasei Microdevices AK8976A

subjects were selected from PhD students of our EE department to perform the experiments during which the data was collected. During the data collection procedure the subjects were asked to walk on a predefined trajectory. The path was 25.65 meter long which has been walked with average of 18 strides (=36 steps). Since we only consider the steps of the foot that the mobile is attached to (the carrier foot), this gives us 180 data samples in different directions and orientations of the phone for examining our uDitect algorithm. Walking on the baseline trajectory is performed while users were carrying two mobile phones. One of the mobile phones had a fixed orientation with user and is placed on the middle of user chest for the other one the users were free to choose the orientation of the phone to place it in their pocket. While the data from device in the pocket is used for direction detection in uDirect, the fixed device has been used for verifying the ambient magnetic noise. Fig.7 shows the trajectory, which consists of 4 sections.

The stance phase for deterministic model is detected using a simple peak detection algorithm. To avoid the confusion of peak detection algorithm with random noise in accelerometer samples average filtering with a window of 10 samples is performed before peak detection. In addition to GPS estimations, the collected data is also processed with PCA based algorithm from [15] for comparison. In order to minimize the noise due to ambient magnetic field and also providing a comparison with GPS, the experiment has been performed in an open space area. At this stage all the analyses were offline processed with Matlab. Results

According to uDirect algorithm the horizontal acceleration at the middle of stance phase can be used as estimation for user facing direction. The top part of fig.8 shows the vertical accelerations (\ddot{V}) during walking toward east (+ 90 degree to North). The local and global minimas are detected via a simple peak detection algorithm. As was mentioned, each subsequent local and global minima shows heel strike (H) and toe off (T) moments respectively and the stance phase is defined as the period of time between each subsequent heel strike and toe off moments. The bottom part of the figure shows the relative deviation of resultant of horizontal acceleration components (\ddot{H}) from North.

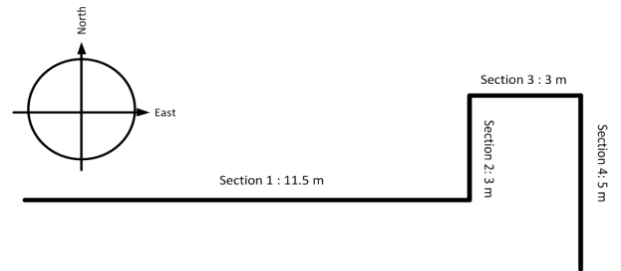


Figure 7. the base line trajectory. Section 1 :11.5 meters west to east, Section 2 : 3 meters south to north, Section 3: 3 meters east to west and Section 4 : 5 meters north to south

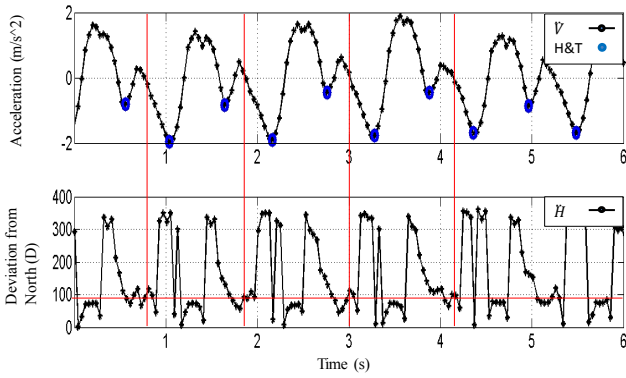


Figure 8. Walking locomotion toward East ,Top part: Vertical accelerations(\ddot{V}) toe off and heel strike moments (H &T) ,for determining stance phase, are detected by a peak detection algorithm. Bottom part: Deviation angle between the horizontal acceleration samples (\ddot{H}) and North direction during walking. The vertical red lines show the middle of stance phases and horizontal red line is aligned with 90 degree deviation, As is shown the samples belong to middle of stance phase are giving the best estimations of user direction.

A comparison between these two parts by following the direction that the horizontal components at the middle) of stance phase (depicted as vertical red lines in fig.8) are making with north direction, confirms our assumptions taken in the analytical approach in the previous section, that the middle of stance phase is the most appropriate time for detecting forward direction. Fig.9 shows the average estimation of uDirect algorithm for all participants for each step (of carrier foot). The proposed model has given very good estimation in section 1 and 4 although its performance is degraded in section 2 and three. Typically the best accuracy is given after the first step and before the last one. Consequently, in short sections such as 2 and 3 which are less than 3 steps the estimations has been degraded compared to other sections.

The phenomena can be explained as a result of different acceleration pattern at the start and end of walking, when the user starts to move and tries to stop respectively, compared to the rest of walking locomotion. Furthermore, when participants get close to the end of each section, they start to gradually turn for the next section which can also add undesirable acceleration components. As the result of the presence of the mentioned components the acceleration pattern is changed which in turn causes confusion of the peak detection and direction estimation algorithms.

Overall, by estimating direction with mean error of 14.2 degree and standard deviation of 13.3 for all fully captured steps, containing 120 data samples excluding the distorted first and the last steps, the evaluation confirms our assumptions about unique characteristics of the middle of stance phase for determining user direction.

In comparison with other available models a system that uses the uDirect algorithm would have some unique characteristics which make it more applicable for pervasive observation.

First, in contrast to contemporary GPS and PCA based models, uDirect performs independent direction estimating on each stride. Consequently, its predictions are prone to sudden

changes in user direction and the process can perform almost simultaneously with user change of walking direction. However, PCA based approaches assume that during each analysis the data is captured when user was moving only in one direction. Therefore, their applications require an additional algorithm to identify the unidirectional walking segments and ideally will give a user direction at the end of each section. In case of GPS approach, the best accuracy obtained from the mobile phone embedded GPS was around 8 meters which limits the its acceptable estimations to only where the walking segment was more than 8 meters (section 1). In addition, in contrary to uDirect, it is well known that GPS based approaches are susceptible to shadowing effect of buildings and cannot be used for indoor applications.

Lastly, by developing a basic direction detection system based on uDirect algorithm and analyzing our experimental data as is shown in fig.10, table.1 and table.2, our initial inspections show that our approach has given more accurate and reliable results compare to standard GPS headings and a PCA based approaches from [15]. The results and representations are described below.

Since PCA based model predictions require all data from a walking section to make their estimation we have averaged our results per each section for the sake of comparison. For this, we have considered all 180 data samples to investigate how accurate estimations performed between the first and the last step can mitigate the less accurate estimations at these steps. From fig.11 it can be observed that for the majority of sections (1, 2 and 4) the uDirect algorithm outperform the PCA based algorithm. However, the accuracy of direction estimations of both algorithms along shorter sections, has significantly degraded compared to the longer sections and here the PCA based approach has shown better performance. The result behind this degradation of accuracy lies in the fact that shorter path contains only two steps which means the results are mainly generated from distorted pattern of first and last steps.

It worth noting the accuracy of detecting stance phases with peak detection algorithm is dependent on the window size of averaging filter. For some participants changing the window size to 5 samples has significantly improved the overall accuracy. In fact, a proper window size seems to be dependent on the magnitude of acceleration during walking. However, in this study our aim was to demonstrate the feasibility of implementing such system and finding the optimum window size has remained an open issue for further studies. Keeping the length of window size equal to 10 for a deterministic model the mean error of different methods for each section are provided for comparison in Table.1. Although we have not implemented an optimum window size the presented results in table.1 confirm that the uDirect approach is still accurate when distances are long enough (typically for more than 2 steps).

Similar to [15], it is also interesting to compare the performance of our developed technique with standard GPS based model when estimating the user direction on our baseline trajectory. Since the best GPS prediction is considered to be for distance more than 8 meters, we have focused our comparison

only on estimations of section 1. The presented results in table.2 shows the difference between mean error and standard deviation of predictions of GPS headings with the model from [15] and uDirect. Here a positive value stands for bigger mean error or standard deviation. It can be inferred from this table that uDirect, when averaged per step, had the most accurate and reliable predictions and although averaging per section has slightly reduced the accuracy, it still remains more reliable than GPS and outperform the conventional PCA based approach.

VI. CONCLUSION AND FUTURE WORK

As basic requirement of a ubiquitous observer a system has to be able to detect the direction of user with minimum user involvement and be flexible enough to gracefully handle the changes in device orientation to minimize user involvement. As the first step towards this goal we have presented uDirect, an approach to determine a user's facing direction with a mobile phone, regardless of the mobile phone's orientation. uDirect calibrates the measurements of the arbitrary orientated mobile phone and performs direction estimation based on acceleration pattern of a human during walking locomotion.

During development of our direction detection approach we have modeled the acceleration resulting from the movement of femur bone during walking locomotion. By considering physiological characteristics of a human's walking pattern we have shown that the horizontal samples during the middle of the stance phase are the most informative samples about a user's forward direction, when the mobile device is placed into user's trouser pocket.

Our evaluations of the algorithm with a simple proof of concept implementation confirmed the assumptions of our analytical modeling concerning the special characteristics of stance phase for direction estimation. In addition, our initial evaluation has shown that the proposed approach outperforms the conventional use of GPS and PCA based techniques when samples are taken from more than 2 steps of walking. However, in shorter sections the performance of the model is degraded due to the change in the pattern of walking acceleration. uDirect estimations are robust to shadowing effects for indoor applications (in contrast to GPS approach) and flexible to frequent change of user direction during walking (in contrast to PCA based models). We are currently working on adaptive adjustments of the filtering window size to improve the peak detections. In addition, in order to improve the performance in shorter sections and also reducing the power consumption as a result of using both magnetometer and accelerometer, we are working on an additional magnetic field tracking scheme. During such scheme once the user direction is recognized in a section with proper length, the further estimations are made by simply tracing the variation of magnetometer sample. The scheme should be able to repeat the direction estimation procedures whenever the device orientation in stationary mode is changed (e.g. the user has used the phone).

The proposed methodology for direction estimation can be further extended to cover other positions of the device in proximity of other segments of body by considering the movement pattern of corresponding body segments. In this regard, our initial inspection has shown successful results when a modified version of uDirect was implemented for the chest pocket position. Other common positions of mobile devices, such as handbags, that are commonly used by female users are to be further investigated in our work.

Finally, there are a various different areas to which our algorithm can be applied. For example, it is easy to develop dead reckoning applications on mobile phones by combining uDirect

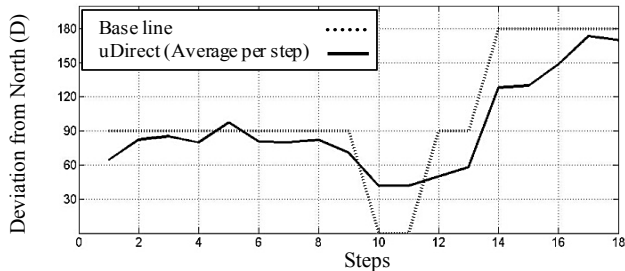


Figure 9. The baseline and uDirect model estimations when is averaged for each step. A window of 10 samples is used for average filtering. Despite of the first and the last steps of each section by exploiting acceleration samples at the middle of stance phase, uDirect algorithm has given accurate estimation of the user direction.

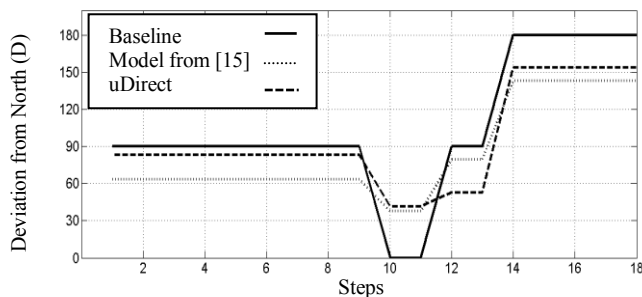


Figure 10. The base line and estimated directions of the trajectory path from model from [15] and uDirect estimations averaged per section. Although, the predictions are degraded in shorter sections from 9th to 13th step, uDirect has provided more accurate predictions for other sections.

TABLE I. ALGORITHMS PERFORMANCE

Techniques	Mean error (Degree)			
	Section1	Section 2	Section 3	Section 4
Model from [15]	26.7	37.6	10.5	37.0
uDirect(average d per section)	18.9	41.7	37.3	35.4

TABLE II. PERFORMANCE COMPARISON WITH GPS APPROCH

Technique	Mean error (Degree)	Standard deviation
Model from [15]	+7.999	+1.253
uDirect(averaged per section)	+0.162	-0.603
uDirect (averaged per step)	-10.5	-11.8

capabilities of facing direction estimation with step recognition techniques. The latter ones can take advantage of information about subsequent heel strike and toe off moments that our algorithm derives during direction estimation. Furthermore, many applications would benefit from the awareness of the facing direction of a user for the inference of user context, in order to adequately render human to computer interaction in distributed smart environments.

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