It's the Human that Matters: Accurate User Orientation Estimation for Mobile Computing Applications

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***Abstract*—Ubiquity of Internet-connected and sensor-equipped portable devices sparked a new wide range of mobile computing applications that leverage the proliferating sensing capabilities of smart-phones. For many of these applications, accurate estimation of the user heading, as compared to the phone heading, is of paramount importance. This is of special importance for many crowd-sensing applications, where the phone can be carried in arbitrary positions and orientations relative to the user body. Current state-of-the-art focus mainly on estimating the phone orientation, require the phone to be placed in a particular position, require user intervention, and/or do not work accurately indoors; which limits their ubiquitous usability in different applications.**

In this paper we present *Humaine*, a novel system to reliably and accurately estimate the user orientation relative to the Earth coordinate system. *Humaine* requires no prior-configuration nor user intervention and works accurately indoors and outdoors for arbitrary cell phone positions and orientations relative to the user body. The system applies statistical analysis techniques to the inertial sensors widely available on today's cell phones to estimate both the phone and user orientation. Evaluation of the system on Android devices at different testbeds shows that *Humaine* significantly outperforms the state-of-the-art in diverse scenarios, achieving a median accuracy of 14° indoors and 15° outdoors. This is 523% better than the-state-of-the-art indoors and 594% outdoors. The accuracy is bounded by the error in the inertial sensors readings and can be enhanced with more accurate sensors and sensor fusion.

I. Introduction

Recent advances in ubiquitous computing highlighted the importance of user direction estimation; it enables plentiful ubiquitous and mobile computing applications such as localization [1]–[4], activity recognition [5], virtual reality, among others [6], [7]. Today's smart-phones are equipped with a number of inertial sensors, e.g. accelerometer, magnetometer, and gyroscope. These sensors provide a measurement for the cell phone orientation relative to the magnetic North. However, users carry cell phones in arbitrary positions and orientations that are typically disoriented with respect to the user (Figure 1). Depending on the phone orientation, rather than the user orientation, can lead to huge errors in many applications. For example, in the popular dead-reckoning localization techniques, e.g. [4], [8], the user displacement obtained from the inertial sensors is combined with the movement direction to estimate the next user location. Erroneous direction estimation,

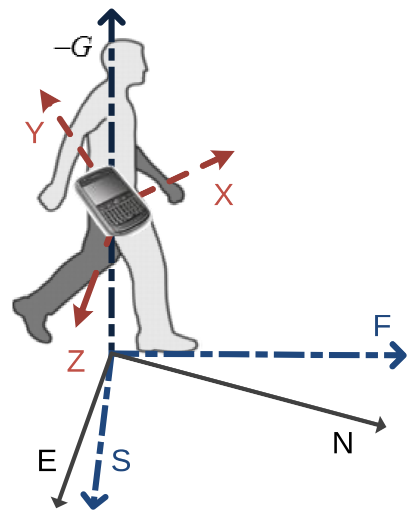


Fig. 1. Different coordinate systems: The phone coordinate system (X, Y, Z) is misaligned from the human coordinate system $(F, S, -G)$, which in turn is misaligned with the world coordinate system $(N, E, -G)$. Note that both the human and world third axis coincide with the negative direction of gravity. The user plane of motion is the (F, S) plane, which is the plane perpendicular to gravity.

just based on the returned phone orientation from the OS API, will result in a large error in localization that accumulates quickly with time. This is especially true for the growing field of mobile applications that do not assume a certain placement or orientation of the phone, e.g. in hand or in pocket, such as crowd-sensing applications.

To overcome these problems and obtain the actual user direction, a number of systems have been proposed [9]–[14]. For example, [9], [10], [13], [14] depend on ***special external sensors*** attached to the user's leg or placed in her pants pocket to detect her orientation. Other systems, e.g. [11], [12], use the inertial sensors in standard cell phones to estimate the user direction. However, these solutions either work only in specific phone positions (e.g. pants pocket [11]), are limited to outdoor environments where the user step pattern is not affected by the indoor magnetic noise [11], or requires special user actions (e.g. [12]). These limit their ubiquitous usability.

In this paper, we present *Humaine*: a system capable of accurately estimating the user orientation in different environments at arbitrary phone positions and orientations without user intervention. *Humaine* starts by fusing the different phone inertial sensors to obtain the phone orientation in the user horizontal plane of motion. To obtain the actual user heading, *Humaine* takes advantage of the observation that the direction of motion is the direction that has the maximum acceleration variance. Therefore, it applies the principal component analysis (PCA) on the linear acceleration readings in the user horizontal plane of motion to obtain the final user heading. *Humaine* further applies different pre-processing and post-processing steps to reduce the noise effect and remove inherent ambiguity in the direction estimation.

Implementation of *Humaine* on Android devices shows that it can estimate the user direction with a median error up to $14°$ indoors and $16°$ outdoors for a variety of phone positions. This is better than state-of-the-art direction estimation systems by more than 523% indoors and 594% outdoors.

In summary, our main contributions are three-fold:

- We present the architecture and details of *Humaine*: a system to detect accurate user orientation using standard cell phones at arbitrary positions and orientations in both indoor and outdoor environments.
- We implement our system on Android-based mobile devices and evaluate its performance as compared to other state-of-the-art systems.
- We provide a thorough study on the effect of different phone positions (in hand, in pants pocket, in bag, in shirt pocket), phone orientations relative to the user body, and indoor/outdoor effect on the different user direction estimation techniques.

The rest of the paper is organized as follows: In Section II, we discuss related work. Section III gives the details of the *Humaine* system. We provide the implementation and evaluation of the system in Section IV. Finally, Section V concludes the paper and gives directions for future work.

II. Related Work

Applications that require the user heading direction estimation, e.g. [4], [8], usually assume that the phone is oriented with the user and depend on the cell phone standard API. This can lead huge errors in case the phone is not aligned with the user. Throughout this section, we discuss the different techniques for user direction estimation that have been proposed in literature.

A. Techniques based on Location Estimation

Frequent logging of user location, e.g. using GPS [15], can provide accurate user direction. In this case, the direction is estimated as the direction of the line joining the last two estimated locations. However, this depends on the availability and the accuracy of the localization system. For example, since the GPS accuracy is low in urban areas [16], the direction estimation is not accurate. In addition, it completely fails in indoor environments.

B. Techniques that use Special Sensors

To overcome this limitation, researchers in [9], [10], [13], [14], [17]–[19] employed other sensors to provide accurate direction estimation. In [17], [18], authors used a wearable camera and analyzed the taken pictures to provide better orientation estimation. Similarly, in [10] authors used an electromyography sensor for walking identification, step detection, and stride length estimation; they also used a 2D compass to estimate the heading. Similarly, [9] used shoe-mounted sensors for displacement computation and estimated the direction using a digital compass. In [13], PCA was used to estimate the heading direction from acceleration measurements from *special sensors*. PCA yields the motion axis that is parallel to the movement direction, but it fails to determine the forward direction itself, leading to a "$180°$ ambiguity problem".

To detect the forward direction, [14] leverages the rotational motion of the sensor; the system exploits the coupling between the rotational motion of the thigh and the device in the pants pocket, as they exhibit a rotation axis approximately orthogonal to the motion axis. Using the rotation matrix output of the sensor, the system calculates the angular movement in a 0.5s span before foot impact (approximately one leg swing). The system requires the movement to be positive, thus the rotation axis is always aligned to the right side of the body. Finally, the system rotates the axis $90°$ in the horizontal plane yielding an approximate direction of the forward motion. All these solutions depend on special external sensors, which limits their ubiquitous deployment. In addition, these sensors usually have higher quality compared to typical phone sensors. Moreover, [13], [14] require the phone to be placed in the pants pocket, reducing their applicability. Finally, [14] is based on detecting the step pattern, whose accuracy is severely affected indoors as we show in Section IV.

C. Techniques based on Cell Phone Sensors

Recently, researchers have focused on using standard cell phones sensors to detect the user heading direction. In [12], the system **assumes that initially the cell phone is in the pants pocket and the heading offset is known**. To infer the user heading direction, the system requires that the user holds the phone at the beginning; hence the phone heading direction is the same as the user. Then the user puts the phone in her pants pocket. The system leverages the periodicity of the leg movement during walking to identify a point during each step where the relative orientation of the phone to the user's body is the same as in the initial standing state – The system identifies it as the point representing the left leg bypassing the right leg while walking. The system uses a particle filter to mitigate the magnetic field noise effect to work indoors effectively. However, this particle filter requires a map of the building, which may not be ubiquitously available especially for crowd-sensing applications.

The uDirect system [11] employs a similar technique to estimate the user direction; They identify a point in the middle between the user's detected heel strike and toe-off moments as the point where the device orientation is close to the device orientation in the standing mode. They detect the user's standing mode when there is an approximate zero variance in the acceleration [20]. Nevertheless, the system requires the phone to be **placed in the pants pocket** and the magnetic field noise makes uDirect practically inapplicable indoors as we quantify in Section IV.

D. Summary

Table I summarizes the differences between *Humaine* and the most relevant state-of-the-art. The current state-of-the-art either require special external sensors, work in a specific phone position (e.g. in pants pocket) or orientation (e.g. oriented phone with the user), require user intervention, and/or works only outdoors. PCA-based techniques proposed in literature [13], [14] are based on special external sensors, assume placement in pants pocket, do not work well indoors, and do not handle the 180° ambiguity problem in the general setting.

Humaine, on the other hand, depends on available inertial sensors in standard cell phones. It is applicable indoors and outdoors for arbitrary phone positions and orientations without any intervention from the user.

III. The *Humaine* System

In this section, we provide the details of the different components of the system; covering the sensor readings preprocessing, the acceleration transformation to the user's plane, detection of the user's motion axis, and finally detection of the user's orientation relative to North. We start by defining the coordinate systems used in the paper, followed by an overview of the system architecture, and finally the details of each module.

A. Coordinate Systems

Figure 1 shows the different coordinate systems used in the paper. The world coordinate system $(N, E, -G)$ is defined by North (N), East (E), and the Earth gravity $(-G)$. We refer to the phone local coordinate system as (X, Y, Z). The user plane of motion is perpendicular to gravity and we are interested in the user forward direction (F). Therefore, the user coordinate system is defined as $(F, S, -G)$.

Table II summarizes all symbols used in this section.

B. System Overview

Figure 2 shows the system architecture. The system detects the orientation, relative to North, of a user that carries a cell phone with her in an arbitrary position using the available cell phone's inertial sensors.

The Sensor Fusion Module fuses the different inertial sensors to obtain the linear acceleration, the phone azimuth direction, and the phone rotation angles relative to the world.

The Preprocessing Module filters the linear acceleration readings to reduce the noise.

The User Direction Estimation Module transforms the linear acceleration readings to the user plane of motion and estimates the user motion axis as the direction with the maximum variance. Finally, the Ambiguity Resolution Module disambiguates the final user's heading direction along the motion axis.

Symbol	Description
$N, E, -G$	The world axes (Figure 1): N points to North, E points to East, and $-G$ is opposite to gravity.
$F, S, -G$	The axes of the user coordinate system (Figure 1): F points in the forward user motion direction, S points towards the side, and $-G$ is opposite to gravity.
X, Y, Z	The axes of the cell phone coordinate system (Figure 5): X points towards the cell phone side, Y points towards the cell phone head, and Z is perpendicular to cell phone screen.
α	The cell phone pitch angle (Figure 5).
β	The cell phone roll angle (Figure 5).
γ	The cell phone yaw angle relative to the North (phone azimuth, Figure 5).
θ_u	The user orientation angle relative to the North.xx arch
$R_A(b)$	Rotation matrix of angle b around axis A.
g	The Earth's gravity acceleration $(9.80665 m/s^2)$.
a_t	Total acceleration affecting the cell phone (Figure 3).
ℓ	Linear acceleration in the phone coordinate system (Figure 3).
$G_m = [g_x, g_y, g_z]^t$	gravity acceleration components in the phone coordinate system (Figure 3).
δ	Noise filter smoothing factor.
w	PCA window size.

TABLE II. Summary of the symbols used with its description.

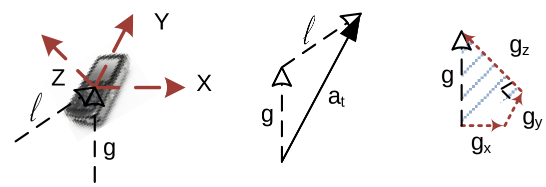


Fig. 3. The total force (a_t) applied to the phone at any time instance is the sum of the gravity acceleration (g) and the linear acceleration (l). The gravity acceleration components in the phone coordinate system are (g_X, g_Y, g_Z).

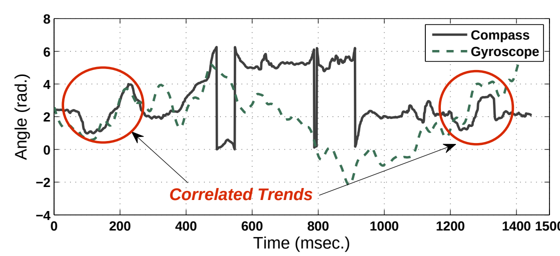


Fig. 4. Example showing leveraging the correlation between the compass and gyroscope sensors to determine when the compass readings are reliable.

C. Sensor Fusion

The system collects raw sensor information from inertial sensors available in the cell phone. In particular, we collect the 3D acceleration, the orientation from the digital compass, and the relative rotation angle from the gyroscope. Sensor fusion is an important step to reduce noise and estimate the quantities of interest. The accelerometer returns the acceleration force applied to the phone. It consists of two components: the gravity and linear acceleration applied to the phone due to its motion (Figure 3). To separate these two components, *Humaine* opportunistically uses the instances when the magnitude of the acceleration vector approximately equals $g(9.80665 m/s^2)$ as the gravity reference. The intuition is that, at these instances, there are no other forces applied to the phone. *Humaine* then uses the gyroscope to track the gravity vector as it moves due to the user movement. Since, we are only interested in the device's acceleration due to motion; this gravity vector is

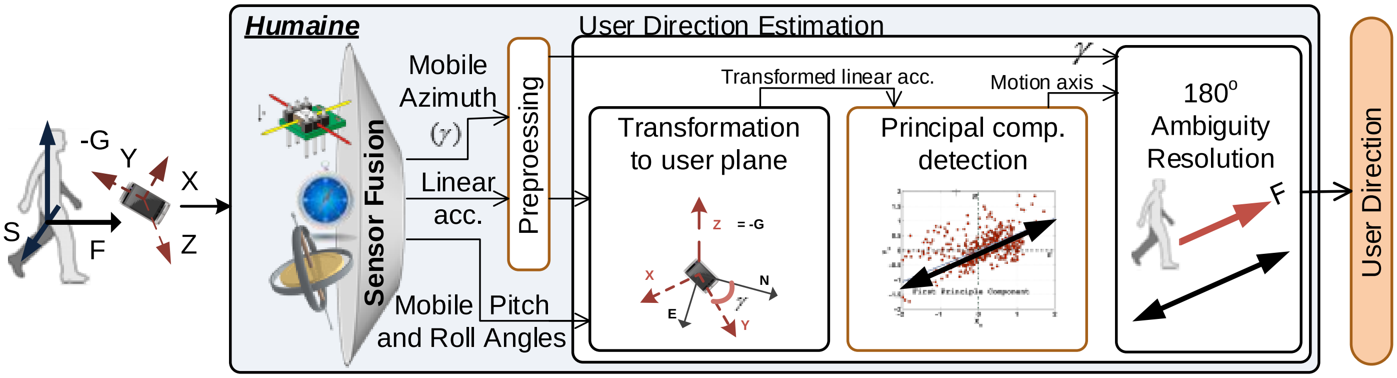


Fig. 2. *Humaine* system architecture — The system takes the raw sensor readings from the user's cell phone and gives the user's direction relative to North.

Criteria \ Technique	Kunze et al. [13]	Steinhoff et al. [14]	uDirect [11]	Fan Li et al. [12]	Humaine
Standard Cell-phones	No	No	Yes	Yes	Yes
Sensor/phone placement	Pants Pocket	Pants Pocket	Pants Pocket	Pants Pocket and in Hand	Anywhere
Assumptions	User moving forward and not changing direction	None	None	Floor-plan is available, initial phone heading offset is known, and phone is stable relative to the leg movement during walking	None
Work indoors	Yes	No	No	Yes	Yes
Evaluation testbed	Outdoors	Outdoors	Outdoors and Indoors	Indoors	Outdoors and Indoors

TABLE I. COMPARISON WITH THE MOST RELEVANT USER ORIENTATION DETECTION TECHNIQUES.

used to to obtain the linear acceleration in the mobile phone coordinate system as described in Section III-E.

As a final note, since the gyroscope sensor suffers from drift, i.e. accumulation of error with time, we fuse it with the compass readings, which has long term stability but suffers from short term magnetic noise, to obtain reliable orientation readings. To determine the points in time when the compass reading is reliable, we depend on the the correlation between the compass and the gyroscope readings (Figure 4). When both sensors exhibit a similar pattern, we declare that the compass reading is accurate and can be used to correct the gyroscope drift.

D. Preprocessing Phase

Humaine estimates the user direction based on processing the linear acceleration vector from raw sensor measurements; These measurements are sensitive to abrupt changes in the cell phone, e.g. due to shaking. To reduce the noise effect, we apply a low pass filter on the linear acceleration measurements $r(i)'s$ with the following equation:

$$s(i) = s(i-1) + \delta.(r(i) - s(i-1)), i > 0$$

Where $s(i)$ is the i^{th} smoothed acceleration signals, $r(i)$ is the i^{th} raw linear acceleration sample, and δ is the smoothing factor. We found that a smoothing factor of 0.25 leads to the best performance as we quantify in Section IV.

E. Estimating Phone Orientation

Users carry cell phones in different positions (e.g. pants' pocket, shirt's pocket, in bag, or in hand). Therefore, the phone can have an arbitrary orientation relative to the user's plane of motion. To estimate the phone orientation, we depend on the estimated gravity acceleration from the sensor fusion module. For ease of illustration, we use Euler angles and rotation matrices to explain how *Humaine* estimates the phone orientation angles around the three main axes; i.e. yaw, pitch, and roll (Figure 5). However, we explain our actual implementation in the next subsection.

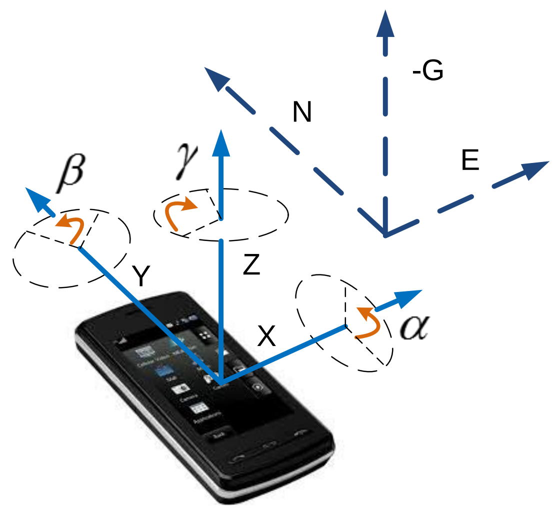


Fig. 5. Different phone orientation angles: pitch (α), roll (β), and yaw (γ). γ is the phone orientation angle relative to North (azimuth angle).

1) Obtaining rotation angles: Let $G_m = [g_x, g_y, g_z]^t$ be the gravity components of the gravity acceleration affecting the phone in its arbitrary location. G_m can be written as:

$$\begin{bmatrix} g_x \\ g_y \\ g_z \end{bmatrix} = R_X(\alpha) R_Y(\beta) R_Z(\gamma) \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix} \quad (1)$$

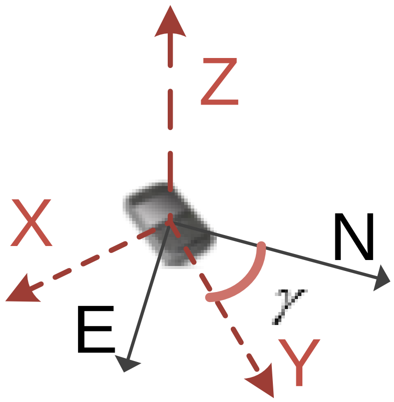


Fig. 6. The phone orientation after applying the rotation matrices $R(-\beta)R(-\alpha)$. The phone Z-axis becomes aligned with $-G$ and the phone rests in the horizontal plane of motion making an angle γ with North (phone orientation angle).

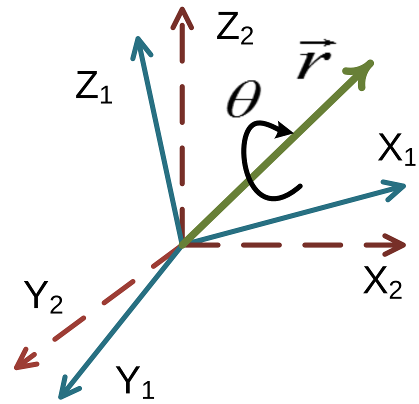


Fig. 7. Transforming between two coordinate systems can be performed using three rotations around the three orthogonal axes by the corresponding Euler angles. This is equivalent to a single rotation around axis $\vec{r}$ with an angle θ.

where $R_A(b)$ is the rotation matrix representing a rotation with angle b around axis A. In particular:

$$R_X(\alpha) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\alpha) & \sin(\alpha) \\ 0 & -\sin(\alpha) & \cos(\alpha) \end{bmatrix} \tag{2}$$

$$R_Y(\beta) = \begin{bmatrix} \cos(\beta) & 0 & -\sin(\beta) \\ 0 & 1 & 0 \\ \sin(\beta) & 0 & \cos(\beta) \end{bmatrix} \tag{3}$$

$$R_Z(\gamma) = \begin{bmatrix} \cos(\gamma) & \sin(\gamma) & 0 \\ -\sin(\gamma) & \cos(\gamma) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{4}$$

To obtain the pitch (α) and roll (β) angles, we multiply both sides of Equation 1 by $R_Y^{-1}(\beta)R_X^{-1}(\alpha)$ and noting that $R_A^{-1}(b) = R_A(-b)$, we obtain:

$$R_Y(-\beta)R_X(-\alpha)G_m = R_Z(\gamma)\begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix} \tag{5}$$

Substituting from equations 2, 3, and 4 we obtain:

$$\begin{bmatrix} \cos(\beta) & \sin(\beta)\sin(\alpha) & \sin(\beta)\cos(\alpha) \\ 0 & \cos(\alpha) & -\sin(\alpha) \\ -\sin(\beta) & \cos(\beta)\sin(\alpha) & \cos(\beta)\cos(\alpha) \end{bmatrix} \begin{bmatrix} g_x \\ g_y \\ g_z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix} \tag{6}$$

From the second and first rows of Equation 6 we get:

$$\tan(\alpha) = \frac{g_y}{g_z} \tag{7}$$

$$\tan(\beta) = \frac{-g_x}{g_y \sin(\alpha) + g_z \cos(\alpha)} \tag{8}$$

To obtain the yaw angle (γ), which is the phone orientation angle relative to North (Figure 6), we leverage the magnetometer signal. In particular, let $M = [m_x, m_y, m_z]$ be the measured magnetic field at the arbitrary phone orientation. Using a similar approach to Equation 5, we get

$$\begin{bmatrix} m_x\cos(\beta) + m_y\sin(\beta)\sin(\alpha) + m_z\sin(\beta)\cos(\alpha) \\ m_y\cos(\alpha) - m_z\sin(\alpha) \\ -m_x\sin(\beta) + m_y\cos(\beta)\sin(\alpha) + m_z\cos(\beta)\cos(\alpha) \end{bmatrix} = \begin{bmatrix} E\cos(\psi)\sin(\gamma) \\ -E\cos(\psi)\cos(\gamma) \\ E\sin(\psi) \end{bmatrix} \tag{9}$$

where E and ψ are the ***unknown*** Earth magnetic field strength and the dip angle of the field measured downwards from horizontal [21] for a perfectly oriented phone, i.e. pointing to North. From the first and second rows of Equation 9 we get:

$$\tan(\gamma) = \frac{m_x\cos(\beta) + m_y\sin(\beta)\sin(\alpha) + m_z\sin(\beta)\cos(\alpha)}{m_z\sin(\alpha) - m_y\cos(\alpha)} \tag{10}$$

Equations 7, 8, and 10 are solved taken into account the sign of the gravity acceleration and magnetometer components to obtain the correct quadrant for the respective angles.

2) Actual implementation: We use unit quaternions to represent the rotation operation in *Humaine* rather than rotation matrices. This representation evolves from Euler's rotation theorem [22], which implies that any rotation or sequence of rotations of a rigid body in a three-dimensional space is equivalent to a pure rotation about a single fixed axis $r = [r_x, r_y, r_z]^t, r_x^2 + r_y^2 + r_z^2 = 1$ by an angle θ (Figure 7). Quaternions give a simple way to encode the rotation operation in 4 parameters, compared to 9 parameters in case of rotation matrices. In addition, quaternions suffer from fewer mathematical rounding defects and are not subject to the gimbal lock problem [22], [23].

The relation between the pitch, roll, and yaw angles obtained in the previous section and the 4D quaternion vector

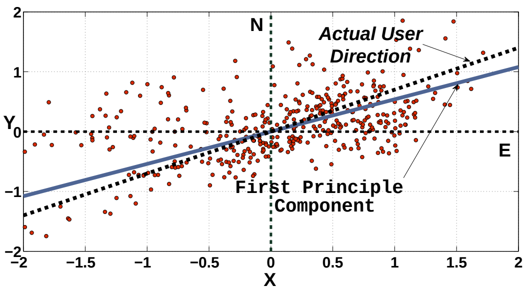


Fig. 8. PCA applied to the linear acceleration samples in the user plane after orienting the phone. The figure shows the estimated as well as the actual user direction.

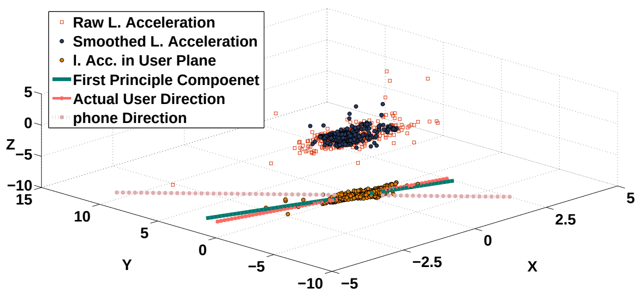


Fig. 9. The figure shows the linear acceleration at different processing steps by *Humaine* to get the motion axis: raw acceleration, de-noised, and transformed linear acceleration.

is:

$$q = \begin{bmatrix} \cos(\theta/2) \\ \sin(\theta/2)r_x \\ \sin(\theta/2)r_y \\ \sin(\theta/2)r_z \end{bmatrix}$$
$$= \begin{bmatrix} \cos(\alpha/2)\cos(\beta/2)\cos(\gamma/2) + \sin(\alpha/2)\sin(\beta/2)\sin(\gamma/2) \\ \cos(\alpha/2)\sin(\beta/2)\cos(\gamma/2) - \sin(\alpha/2)\cos(\beta/2)\sin(\gamma/2) \\ \sin(\alpha/2)\cos(\beta/2)\cos(\gamma/2) + \cos(\alpha/2)\sin(\beta/2)\sin(\gamma/2) \\ \cos(\alpha/2)\cos(\beta/2)\sin(\gamma/2) - \sin(\alpha/2)\sin(\beta/2)\cos(\gamma/2) \end{bmatrix} \quad (11)$$

F. Obtaining the User Motion Direction

To obtain the user motion direction, we transform the linear acceleration, which is the acceleration due to all forces applied to the phone except gravity, to the user motion plane. This is achieved by applying the quaternions to the linear acceleration vector (ℓ).

Once the phone linear acceleration is transformed to the user plane of motion, what remains is to obtain the user direction relative to North. Figure 8 shows that even though the phone has been oriented to North by applying the rotation angles, the linear acceleration samples are not aligned with North, but rather with the user direction. *Humaine* exploits this observation to detect the user direction as the direction that has the maximum variance. To obtain this direction, we apply PCA to a window of the transformed linear acceleration values of size w. The first principal component is the direction of maximum variance. Figure 9 shows the acceleration signal at different stages of processing by *Humaine*.

G. Resolving Ambiguity

The obtained direction through PCA cannot differentiate between the actual user direction and its opposite, i.e. θ_u and $\theta_u + 180$. To resolve this ambiguity, we use the phone orientation angle (γ) as a hint and choose the PCA output direction that is closest to γ. This will work as long as the difference between the phone orientation and the user orientation is within than $\pm 90°$, which is the typical case.

IV. Evaluation

We implemented *Humaine* on different Android devices including Samsung Galaxy Nexus S, Samsung Galaxy Tab 10.1, and an Asus Nexus 7 tablet. We evaluated the system in different indoor and outdoor environments while placing the phones at different positions including shirt pocket, pants pocket, in bag, and in hand; as well as covering different phone orientations relative to the user direction of motion. To evaluate the system applicability under different magnetic field characteristics, we used a number of testbeds including different rooms at a typical home environment, a college library, office room, garden, different wide and narrow streets, among others. To obtain ground truth, we mark the user path on the ground and used the path orientation from Google Maps as the ground-truth.

For the rest of the section, we start by evaluating the effect of the system parameters on accuracy, mainly the noise filter smoothing factor (δ) and the PCA window size (w), then compare the performance of the end-to-end system, in terms of orientation estimation error and latency, with the Android API and the uDirect system [11].

A. Performance of the Different System Parameters

1) Smoothing factor effect (δ): Figure 10 shows the effect of the low pass filter smoothing factor (δ), applied on the linear acceleration to reduce the noise effect, on the orientation estimation accuracy (Section III-D). The figure shows that using a high value for δ leads to ignoring the samples history while using a low value ignores recent values; both are not good for the system performance. We choose $\delta = 0.25$ as it gives the best accuracy eliminating noise without affecting the acceleration signal.

2) PCA sliding window size (w): Figure 11 shows the effect of the PCA sliding window size (w) described in Section III-F on both indoor and outdoor experiments. As expected, the user's orientation estimation improves as we increase the window size. However, a larger window size will cause latency when the user changes her direction. Hence, we choose a window size of 3 seconds.

B. Comparison with Other Systems

In this section, we compare the performance of *Humaine*, in terms of heading estimation error and latency in direction change estimation, to uDirect [11] and the Android API. uDirect uses inertial sensors available on the cell phone to estimate the user direction without prior requirements or assumptions similar to *Humaine*. However, it employs a step detection technique to detect the user heading. On the other hand, the Android API is the default heading estimation technique

Technique	User Heading Estimation Error *Indoors* (degrees)											
	Pants pocket			Shirt pocket			Hand held			Bag		
	50%	75%	Max.	50%	75%	Max.	50%	75%	Max.	50%	75%	Max.
Humaine	21	31	55	9	16	45	12	19	30	17	24	40
uDirect	30 (42.9%)	50 (61.3%)	145 (163.6%)	103 (1044.4%)	142 (787.5%)	180 (300.0%)	102 (750.0%)	141 (642.1%)	180 (500.0%)	90 (429.4%)	137 (470.8%)	175 (337.5%)
Android API	58 (176.2%)	63 (103.2%)	180 (227.3%)	125 (1288.9%)	165 (931.3%)	180 (300.0%)	52 (333.3%)	62 (226.3%)	100 (233.3%)	42 (147.1%)	130 (441.7%)	180 (350.0%)

TABLE III. COMPARISON BETWEEN *Humaine*, ANDROID API, AND UDIRECT [11] IN ***indoor*** ENVIRONMENTS. PERCENTAGES DEGRADATION ARE CALCULATED RELATIVE TO *Humaine*.

Technique	User Heading Estimation Error *Outdoors* (degrees)											
	Pants pocket			Shirt pocket			Hand held			Bag		
	50%	75%	Max.	50%	75%	Max.	50%	75%	Max.	50%	75%	Max.
Humaine	24	30	55	15	25	55	12	18	30	13	24	50
uDirect	25 (4.2%)	40 (33.3%)	120 (118.2%)	122 (713.3%)	155 (520.0%)	180 (227.3%)	95 (691.7%)	140 (677.8%)	180 (500.0%)	82 (530.8%)	121 (404.2%)	180 (260.0%)
Android API	57 (137.5%)	69 (130.0%)	180 (227.3%)	87 (480.0%)	157 (528.0%)	180 (227.3%)	40 (233.3%)	49 (172.2%)	180 (500.0%)	36 (176.9%)	47 (95.8%)	180 (260.0%)

TABLE IV. COMPARISON BETWEEN *Humaine*, ANDROID API, AND UDIRECT [11] IN ***outdoor*** ENVIRONMENTS. PERCENTAGES DEPREDATION ARE CALCULATED RELATIVE TO *Humaine*.

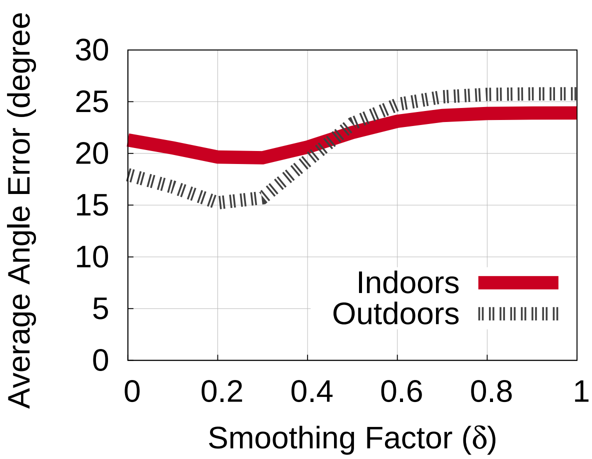


Fig. 10. Effect of the low pass filter smoothing factor (δ) applied to the linear acceleration.

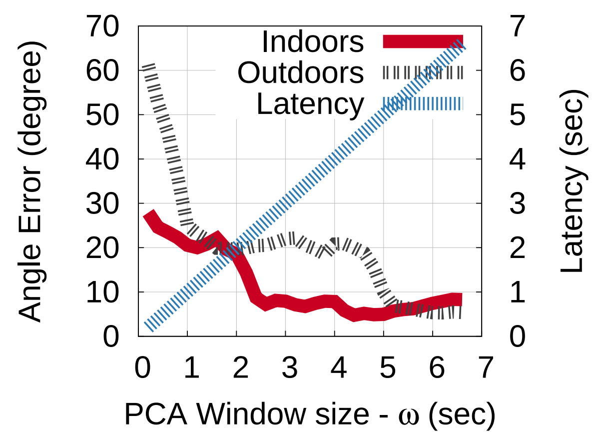


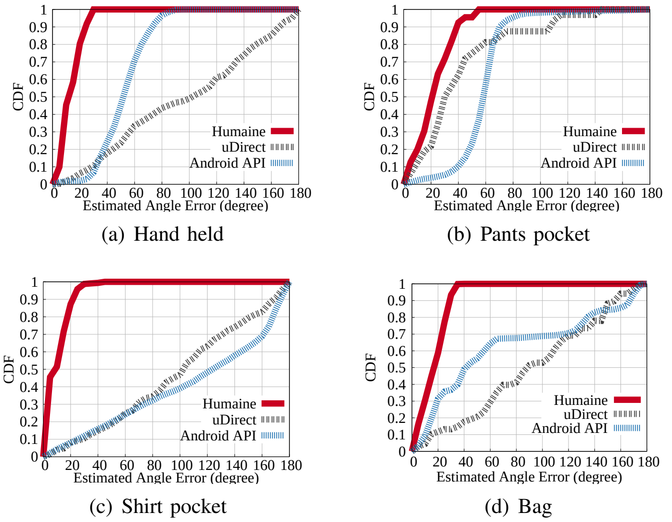
Fig. 11. Effect of the PCA sliding window on the orientation estimation accuracy and latency.

available on Android phones and has been used by a number of systems, e.g. [4], [8], to determine the *phone orientation*, rather than the human orientation.

1) User heading estimations error: Figures 12 and 13 show the CDFs of the user orientation estimation error for the three systems—*Humaine*, uDirect [11], and the Android API—indoors and outdoors respectively for the different cell phone positions. Tables III and IV summarize the results.

The results show that *Humaine* gives the best accuracy in all cases. Since uDirerct depends on estimating the user steps, it is sensitive to magnetic noise in the environment, e.g from electric power cables and metallic objects, that significantly affect the step pattern. For example, Figure 14 shows an example of the user step patterns in indoor and outdoor environments. The figure shows that the step pattern is noisy in indoor environment, significantly affecting uDirect accuracy. Moreover, step detection requires the phone to be carried in the pants pocket, limiting uDirect applicability and affecting its accuracy in other positions. The Android standard API, as it does not estimate the user heading, has the worst accuracy, especially in the shirt pocket as this is the position where the cell phone vertical orientation relative to the users direction leads to the maximum error.

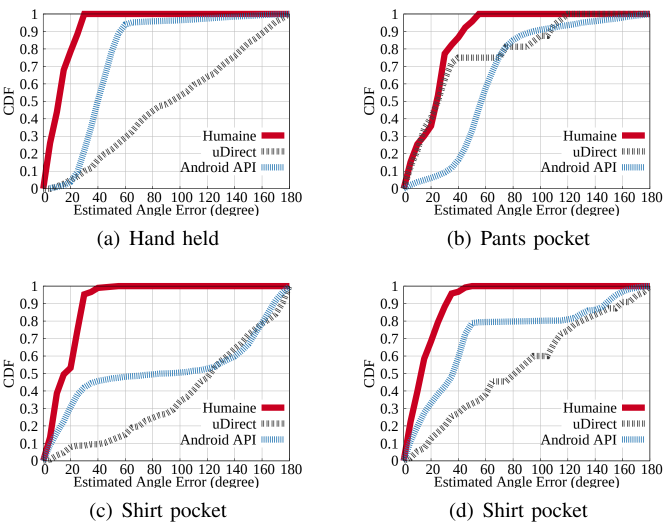
2) Performance in a continuous trace: Figures 15 and 16 show the trajectory of the experiments to examine the effect of changing the direction on *Humaine* and uDirect [11] during a continuous trace for both indoor and outdoor testbeds. Table V summarizes the results. For both cases, the phone was placed in the pants pocket for both system *as uDirect does not perform well in other cases, i.e.* ***this is the best case scenario for***



(a) Hand held (b) Pants pocket

(c) Shirt pocket (d) Bag

Fig. 12. CDF plots comparing *Humaine*, uDirect [11], and Android API *indoors*.



(a) Hand held (b) Pants pocket

(c) Shirt pocket (d) Shirt pocket

Fig. 13. CDF plots comparing *Humaine*, uDirect [11], and Android API *outdoors*.

Environment	Indoors			Outdoors		
	Min	Average	Max	Min	Average	Max
Humaine	0.022	20.72	100.21	0.007	11.86	95.13
uDirect	1.763	22.49	91.69	0.111	17.41	111.17

TABLE V. SUMMARY FOR THE CONTINUOUS-TRACE EXPERIMENTS

uDirect as shown in the previous section. The results confirm that *Humaine* can smoothly track the user heading in both indoors and outdoors environments with most of the errors at the instances of direction change. Note that the latency is **not** captured in the accuracy results in Table V, highlighting that *Humaine* can provide even better accuracy for applications that can tolerate delay. In addition, uDirect accuracy is significantly affected in indoor environments due to the noise affecting the step detection (Figure 14).

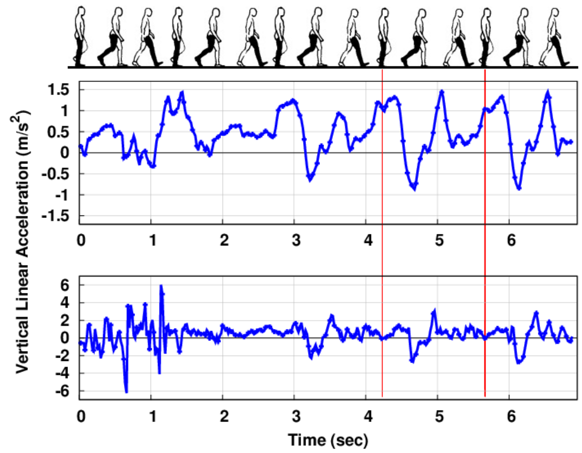
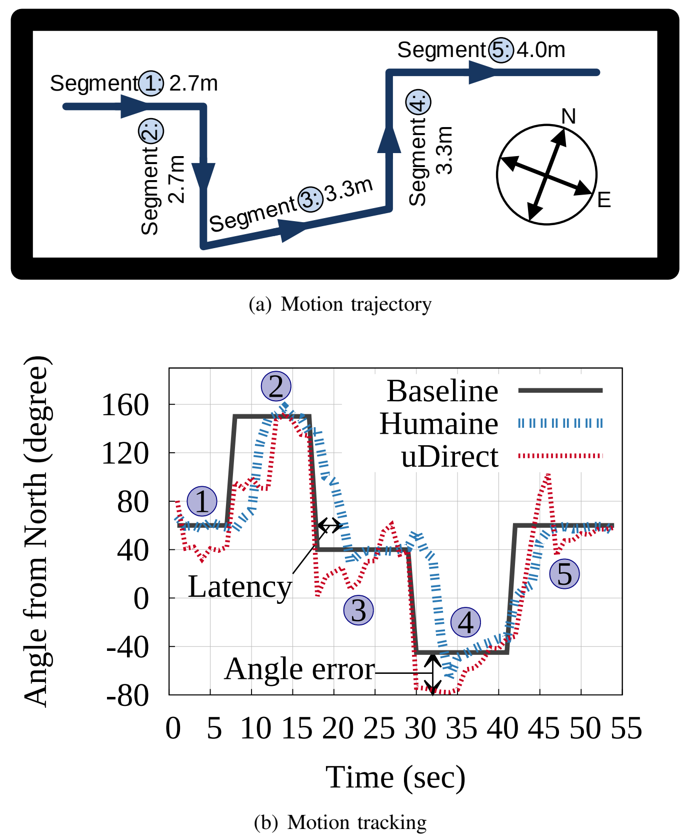


Fig. 14. The vertical acceleration used by uDirect [11] to determine the stance phase. Due to magnetic noise indoors, the step pattern is deformed; explaining its performance degradation indoors.



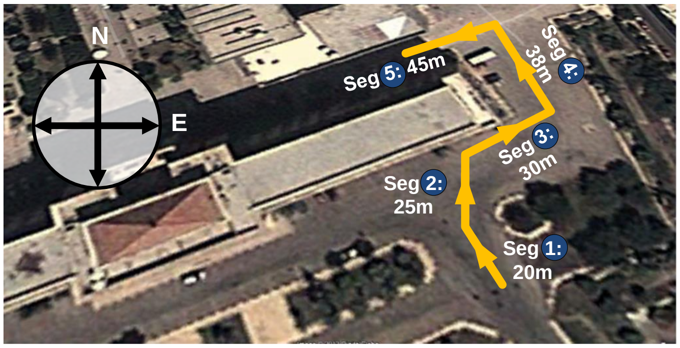
(a) Motion trajectory

(b) Motion tracking

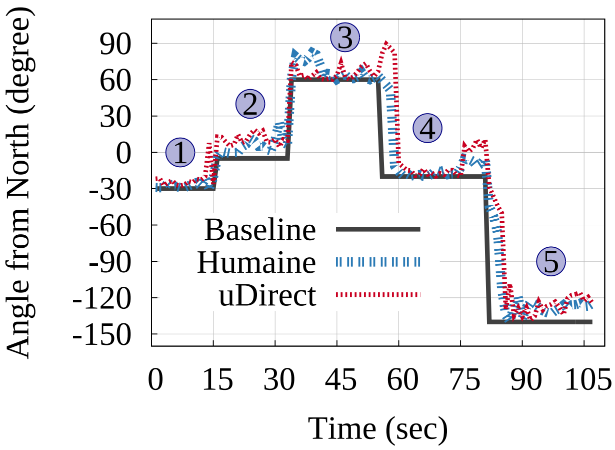
Fig. 15. Tracking performance for *Humaine* and uDirect [11] for a continuous motion trace in an indoor environment.

V. Conclusion

We introduced *Humaine*, a system for robustly estimating the orientation of users carrying cell phones, suitable for new emerging crowd-sensing applications where the user has the freedom to have her phone in any arbitrary position or orientation. It utilizes the phone inertial sensors and applies the PCA technique effectively to detect the user direction.



(a) Motion trajectory



(b) Motion tracking

Fig. 16. Tracking performance for *Humaine* and uDirect [11] for a continuous motion trace in an outdoor environment.

Implementation of *Humaine* on Android devices shows that the system works accurately indoors and outdoors, without user involvement or prior configurations. *Humaine* achieved a median accuracy of $15°$ indoors and $14\circ$ outdoors; which is 523% better than uDirect [11] indoors and 594% outdoors. Currently, we are extending the system in different directions including employing other sensors available on the cell phone, e.g. the camera, opportunistically for a more accurate direction estimation, duty-cycling the sensors for further energy efficiency, dynamically adapting the system parameters, among others.

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