Dead Reckoning from the Pocket – An Experimental Study

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***Abstract*—Modern mobile phones enable absolute positioning based on GPS or WiFi. However, incremental positioning based on dead reckoning is an interesting source of complementary information, e.g., for indoor positioning or for filling in reception gaps. In the literature however, reasonable dead reckoning accuracies have been reported for fixed and typically a priori known device placements only, e.g., on the hip. Therefore, this paper contributes an experimental study of several published as well as novel approaches for dead reckoning in a scenario with unconstrained placement of a device in the user's trouser pockets. Utilizing the movement of a sensor in a trouser pocket due to body motion, we estimate the user's walking direction and steps robustly for arbitrary placements in the pocket and without additional body-worn sensors. We evaluate these methods on a large dataset of 23 traces of 8 different persons, and compare different approaches.**

***Keywords*-dead reckoning; pedestrian positioning; wearable computing**

I. Introduction

Dead reckoning (DR) presents an interesting, incremental positioning modality for pedestrians, complementary to absolute positioning of modern mobile phones (GPS, WiFi, Bluetooth and others). Many location aware applications can profit from greater accuracy and indoor availability, that can be achieved by combining DR with absolute positioning modalities. While dead reckoning is limited for long-term use due to error accumulation, it can achieve high short- to mid-term accuracy, and can be used to gap non-availability phases (e.g., indoors for GPS or WiFi-gaps in less populated areas). Kalman [1] and particle filters [2] are a natural choice to fuse these complementary sources of information for position estimation.

Dead reckoning approaches consist of two basic components, namely step detection and motion direction estimation. For step detection/counting, most pedometer applications rely on body-affixed sensors on a specified body position; additionally, existing DR approaches (e.g., [3], [4], [2]) depend on an a priori known and stable fixture on the body for motion direction estimation, typically dorsally on the hip or on the feet. A major drawback of these positions are that they do not coincide with positions where people already carry devices such as their mobile phone.

Today, dead reckoning has not been adopted widely as a position estimation modality as reasonable accuracies are reported only for fixed and often a priori known positions of the DR device. Our goal is to enable dead reckoning from a standard device such as a sensor enriched mobile phone and start from the hypothesis that more natural device positions – such as the user's pocket – are more realistic and less obtrusive to enable user acceptance of DR. The main contribution of the paper is an experimental evaluation of previously proposed as well as novel algorithms to estimate the user's motion and position incrementally in a scenario of a sensor-enriched mobile phone placed in the user's pocket. In this paper we concentrate on the trousers' front pockets as it is a common location for carrying a mobile phone especially for young males [5]. Due to phone and pocket shape, the device's position inside the pocket is quite stable and the motion/rotation is coupled with the thigh motions [6], [7], making it a promising place for a DR approach. By using the global orientation estimate of our inertial sensor we can translate the measurements into a global orientation frame. This makes our approaches basically independent to the actual placement within the pocket.

Different approaches have been proposed for dead reckoning. It is important to note that most published papers and results concentrate on a single user and/or a few traces for evaluation only. This makes it close to impossible to compare the various approaches and to judge the respective strengths and weaknesses for larger-scale deployment. In contrast, this paper contributes a larger dataset for evaluation consisting of 23 traces, from 8 users and 11 different trousers (for a total of 30km path length) that will be made publicly available.[1] Additionally, we conduct and discuss an in-depth analysis of various published as well as novel algorithms for dead reckoning from the pocket.

An important result of this paper is the general feasibility of DR for a typical placement of a phone. Interestingly, the resulting accuracy for the best approach are only slightly worse than for DR using a well calibrated, dorsally fixated sensor. These results are highly encouraging and suggest to extend DR approaches to more challenging scenarios and placements, and also to further improve the results, e.g., by fusion with other positioning methods and/or further constraints given by a map or floorplan.

[1]online available on http://www.mis.tu-darmstadt.de/datasets

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II. Related Work

Many approaches exist for pedestrian dead reckoning with sensors fixed on the body (e.g., on the hip) both in commercial research, e.g., Honeywell DRM [8], [3] and Vectronix DRC [4], [9], as well as in academic research [10], [11], and often in combination with fusion of GPS in outdoor scenarios. Also combinations with alternative outdoor positioning methods such as WiFi and visual positioning have been proposed [12]. Those approaches typically rely on the firmly body affixed sensor to obtain a reliable estimate.

A number of different approaches employ foot-mounted sensors. [13] and [14] combine step detection on the foot with direction measurements of an additional body fixed sensor. [15] and [16] use double integration of the acceleration signal of the foot mounted sensor only, employing zero velocity updates in phases of ground contact to counter error accumulation. [2] and [17] combine such an approach with map matching in a particle filter to enable accurate indoor positioning. Also sensors on different locations have been investigated, such as mounted on a helmet [18] or in a backpack [14].

More closely related to our work are [6] and [19], which also work with sensors placed freely in a trouser pocket. More specifically, [6] uses sequences of the user's headings, extracted with PCA on Gyroscope measurements projected to a global frame, to learn and recognize predefined transitions indoors. [7] also uses thigh rotation from accelerometer/gyroscope sensors placed freely in the trouser pocket – albeit complemented with a belt worn compass – for recognition of indoor transitions.

[19] infers the horizontal device orientation to the body from the user's walking motion, employing PCA on the acceleration signal projected to a horizontal plane estimated from the gravity vector. A similar use of PCA can be found in [20] to estimate the user's motion axis from a hip mounted sensor with unknown initial position.

Given the different nature of the approaches, scenarios and calibration/fixture requirements, the accuracies reported in product descriptions and research papers cannot be compared directly. For completeness and discussion we cite several accuracies reported before. For a dorsally hip mounted sensor, Honeywell states for the DRM-5 [8] a "typical accuracy of 1-2% distance traveled" in dead reckoning mode, while [21] has shown for an older model 5% under certain constraints. The Vectronix DRC [4] is specified with less than 5% of distance traveled, and [12] reported an median error of 3.2% distance traveled on inner city traces for this device. [18] concentrates on the errors introduced of step length estimation and reports errors in path length less then 5,4% of traveled distance for the neural network based estimation approach, comparable to the results of 1-2% error in [22] for a hip mounted sensor and GPS trained model. All these approaches assume an accurate calibration for angular offset of the sensor to the body.

[14] measures a final 39m error on a 131m forest path for backpack placement with a standard deviation of 22,7m over a set of sample points; for foot-mounted sensors in combination with a firmly attached compass on the shoulder a final error of 4m on a 126m garden path is reported, with sampled standard deviation of 2.2m, and for combination with clothing attached compass 52m final error and 19.9m standard deviation.

[2] report for their foot mounted indoor system, which employs mapmatching in an particle filter, an average tracking error of 0.5m for 75% of time and 0.73m for 95% of time after an initialization phase.

III. Approach

The following describes the various approaches evaluated in our experiments. We also introduce the selected, largely device orientation independent features that we use for step detection and direction estimation.

A. Sensor data.

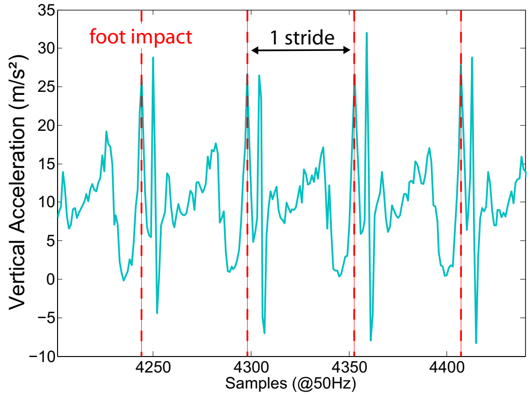
To measure acceleration and rotation in a global coordinate frame, we employ XSens MTx inertial measurement units (IMU) [23] which provide inertial data as well as a global 3-D orientation estimate for the sensor. According to the specification of the manufacturer we can assume a typical dynamic accuracy of 2° RMS for the sensor's orientation output. By directly using the orientation estimate and transforming the inertial measurements from the sensor coordinates to the global frame we obtain measurements largely independent of the specific position of the sensor in the pocket.

B. Step Detection.

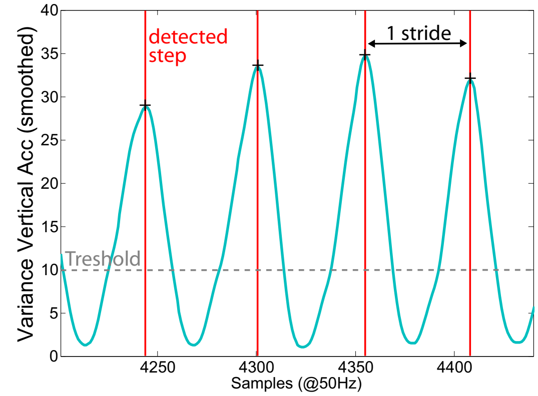
To detect footsteps we empirically found that peaks in the variance of acceleration in the global Z-axis are a robust feature to detect steps of a given leg. This feature can even benefit from device movements due to loose pocket placement (short high pos./neg. peaks after step impact, c.f. 1(a)). We pre- and postprocess the signal with a medianfilter for noise removal, and calculate the variance over sliding windows of 0.15s, and introduce a threshold to avoid spurious step detections from small peaks, as shown exemplary in Fig.1(b).

C. Motion axis estimation.

To determine the user's direction of movement, we first estimate the motion axis of the user, and then determine the forward direction of the user. To estimate the motion axis we explored different approaches, which base either on rotation or on acceleration of the pocketed sensor.



(a) Vertical acceleration of pocket sensor for 4 strides.



(b) Postprocessed variance signal and peak detection

Figure 1. Step detection by peak and threshold on acceleration variance on global Z-axis

1) Rotational approach: This method is based on the rotational motion of the sensor and exploits the coupling between the rotational motion of the thigh and a device in the trouser pocket ([6], [7]), since the latter exhibits also a rotation axis approximately orthogonal to the motion axis. Using the rotation matrix output of the sensor, we calculate the orientation change within 0.5s intervals (approximately one leg swing) and represent it in Euleraxis/Angle form (as shown in Fig.2, Fig.3(a)) To gain a stable direction estimate of the user's motion, we align in postprocessing the axes/angles consistently to avoid flipping due to 180° ambiguity, and average the rotation axes over a one second window (50 samples), weighted by the observed angle (Fig.3(b)) In this way we obtain a stable estimation of an orthogonal axis to the users motion direction, employing the orientation output of the sensor only.

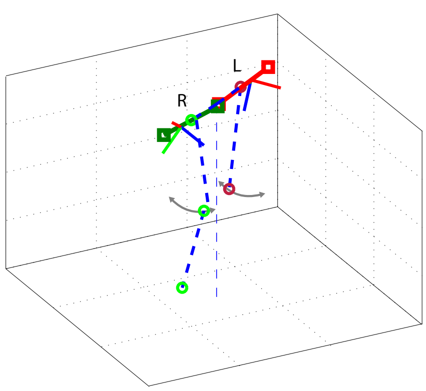


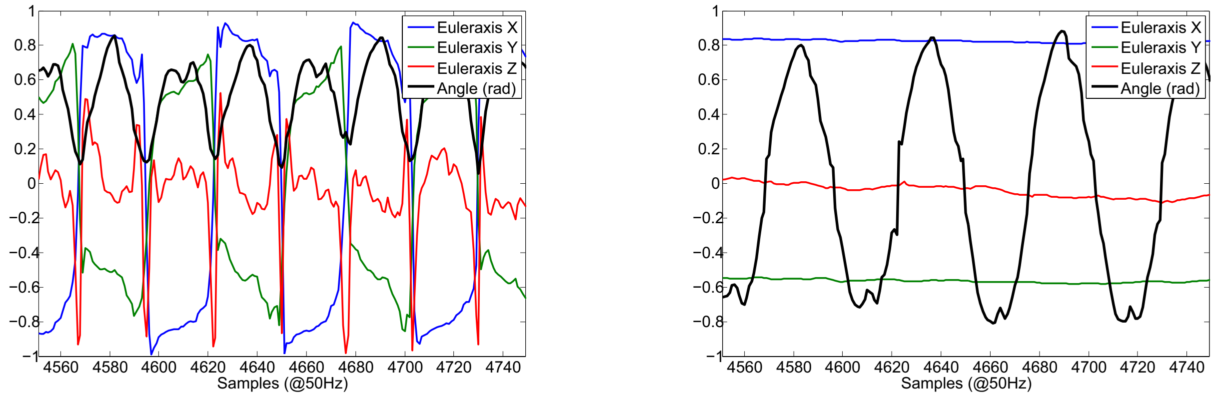
Figure 2. Euleraxis for left and right sensor in partial body model

2) PCA-based approaches: The remaining approaches utilize the fact that the motion axis of the user correlates with the axis of highest variance in horizontal acceleration (respective rotation), which can be determined by principal component analysis (c.f. [19], [20], [6]). In our evaluation we use four different PCA-based variants to obtain the user's motion axis:

- **PCA2D** Applying PCA in 2s windows to the 2D acceleration axes obtained by projection to the global horizontal plane. A window size of 2 seconds, typically containing 2 strides, was found in our evaluation as a good compromise between directional stability and ability to follow quick turns. Fig.4(a) shows an example for this extraction of eigenvectors.
- **PCA2Df** Same as PCA2D, but lowpass filtered at 5Hz to remove noise before applying PCA. A 5Hz mean filter has shown best results in a series of tests basically removing "shaking" noise but retaining acceleration signals due to body motion.
- **PCA3Df** Applying PCA to 3D acceleration axes (transformed to global frame), and subsequent projection of the 3^{rd} eigenvector (smallest eigenvalue) to the horizontal plane. Fig.4(b) shows an example for this method.
- **gyroPCA** We also included an approach described in [6], which relies on PCA on the gyroscope measurements in global frame to extract the relative orientation of a user over time. This approach has proven successful to detect indoor transitions between places.

While in PCA2D and PCA2f the first eigenvector (largest eigenvalue) give directly an estimate of the motion axis, we chose for PCA3Df the 3^{rd} eigenvector, as 1^{st} and 2^{nd} eigenvector have shown to be unstable due to high variance in the whole sagittal plane (vertical plane through the body in forward direction). The 3^{rd} eigenvector (smallest eigenvalue) is orthogonal to this plane, thus to the motion axis.

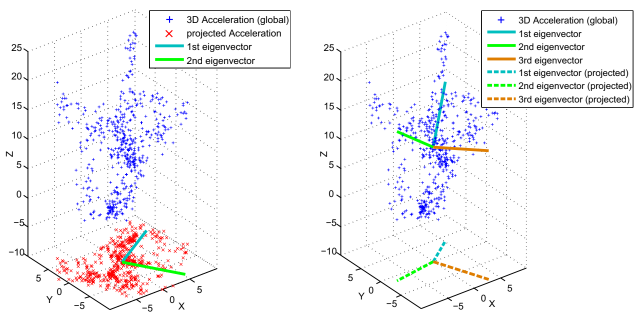
To solve the 180° ambiguity inherent in the results of all approaches above, we align them with help of the forward detection to a consistent direction.



(a) Rotation (in Euleraxis and angle representation) extracted from sensor orientation in 0.5s interval

(b) Postprocessed estimate for rotation axis and angle

Figure 3. Extraction of rotation axis and angle for rotational method and forward detection. 3 strides shown.



(a) PCA2D

(b) PCA3D

Figure 4. Extraction of motion direction with PCA (global coordinate system shown).

D. Forward Detection.

As the estimates of the user's motion axis are not directed, we need to subsequently determine the actual forward direction of the user on the motion axis. A first approach by integration of the acceleration signal in global frame did not yield a robust estimate. Therefore, we decided to use the angular movement in a 0.5s span before foot impact (c.f. 3(b), which we require to be positive, thus aligning the rotation axis always to the right side of the body. A rotation of $90°$ in horizontal plane yields then an approximate direction of the forward motion, and is used to flip the $180°$ ambiguous motion axis estimates accordingly to obtain a forward direction.

E. Step length.

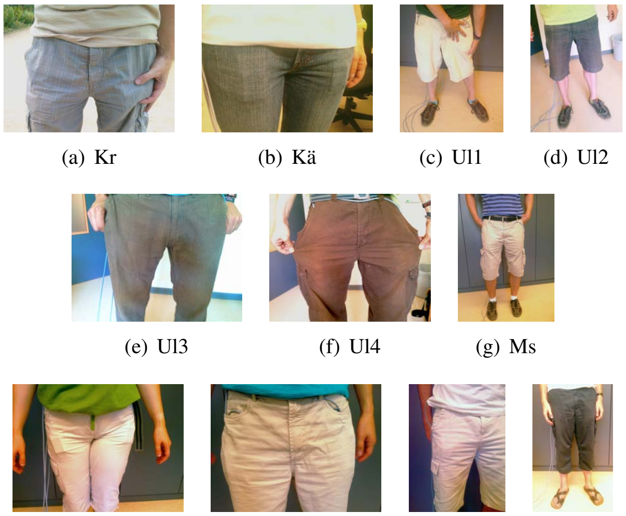
Even though the participants in our test were allowed to walk freely with their chosen speed, we encountered within a trace only small variance in step frequency, and therefore step length [24]. Thus we decided to use a fixed step length per track, which we manually derive from ground truth, to calculate steps in forward direction. We will see in the results later, that the angle error is the dominating error source. While the error due to step length estimation is difficult to analyze, it appears to be in the same order of magnitude as the ground truth accuracy itself. As steplength-stepfrequency ratio is generally user-dependent and influenced by many factors, e.g., body height, slope of track and even the type of boots, we propose an calibration with help of other positioning modalities such as GPS for a more advanced estimate in future work.

IV. Experiments and Results

A. Setup and Recordings.

In initial experiments we fitted an XSens MTx sensor [23] with a Bluetooth module and a battery to a mobile phone sized package, placed them freely in the trouser pockets and compared the measurements to cabled sensors of the same model, fitted to the same mobile phone sized packaging. Once settled, cabled and wireless sensors exhibit a similarly stable position within the trouser pocket, and no characteristic differences in motion are observable. In contrast, different persons, differently tight trousers and different pocket shapes showed significant influence on the sensors readings in our initial experiments. Thus we decided to use the cabled sensors for the recording of the dataset presented here, as they were generally more reliable and better calibrated than the wireless converted version.

Overall we recorded 23 traces from 8 persons, outfitted with sensors in the front pockets; of those, 12 traces were recorded on a round course in a park (c.f. Fig.6 (left half) 870m length), which is walked first anti-clockwise, includes then a turnaround over the start point, and is walked in opposite direction afterwards; the other 11 traces were recorded on a shorter but more complicated track in a garden (c.f. Fig.6 (right half), 415m length). For 6 subjects both tracks were recorded (Kr, Ms, Se, Pa, Uf, Ch), one subject (Kä) was twice recorded in the park on different days and once in the garden, and one subject (Ul) was recorded for



(a) Kr (b) Kä (c) Ul1 (d) Ul2

(e) Ul3 (f) Ul4 (g) Ms

(h) Sa (i) Pa (j) Uf (k) Ch

Figure 5. Trousers of the different subjects in the dataset

both tracks with 4 different trousers (Ul1-Ul4). On all tracks we placed a sensor freely in the left and right pockets, and fixed an additional sensor dorsally on the back for ground truth with a conventional dead reckoning implementation.

We show in Fig. 5 the variety of trousers in the dataset, ranging from tight Jeans to baggy shorts. The most close-fitting trousers were worn by our female subjects Kä(b) and Sa(h), while Pa(i), Ch(k), Uf(j), Ul2(d), Ul3(e) and MS(g) represent normal summer wear and Kr(a), Ul4(f) and Ul1(c) are examples for more loose/baggy trousers. Especially in the last 2 examples the sensors had quite some space to move within the pocket as the inner pocket was not pressed to the leg by the trouser, while in the close-fitting trousers the sensor had steady contact to the thigh.

B. *Evaluation methodology.*

For ground truth more accurate than GPS and to allow for a 'per step' error measure, we implemented a DR approach with a dorsally mounted sensor and dynamic step length adaption according to [25], using the vertical variance of the acceleration signal. The angular body offset and parameter for personal step length were determined manually for each trace, yielding results comparable to commercial solutions such as [4] in our experiments. In contrast to the approaches with a pocket sensor, the dorsal placement allows for detection of steps of both feet.

To provide a continuous ground truth position and as the moment of step detection can vary between pocket and dorsally mounted vector, we apply linear interpolation to the positions given by the accumulated steps. Due to imperfect fixation of the sensor to the body and other error sources such as magnetic deviations, e.g., due to buildings, we have to consider an angular error in the order of 1-5deg for northing, and few percent of distance traveled for path length in ground truth.

To compare the different methods, especially in terms of orientation estimation, we consider on the one hand the resulting error on the map introduced per step, and on the other hand the angular error between dorsally fixed sensor and the orientation estimate from the pocket sensor. More precisely, we consider the deviation from ground truth within each stride, i.e. the absolute error introduced within each heel-down to heel-down of the same foot compared to the interpolated ground truth position. For the absolute error per step the directional error is the dominating error source, but nevertheless step length variation or inaccurately detected forward directions also influence the error. As orientation estimation is the main interest in this paper, we determine also how well the estimated orientation from the pocket sensor correlates with the orientation of the ground truth.

C. *Results Overview.*

Table I gives a condensed overview of the error for the different methods, averaged over the whole dataset of 23 traces and the sensors in both trouser pockets each (summing up to 30km overall trace length). The methods based on PCA of the acceleration signal obtain the best results, with the overall best results for PCA2Df, which is 2 dimensional PCA of the 5Hz lowpass filtered and ground plane projected acceleration signal. With this method we obtain orientation estimates with an average median orientation error of 5.7°. This is also the main source for the average median 12.8 cm deviation per step and equates to 8% error of way traveled. Even for 75% of the steps the error stays below 15% of way traveled.

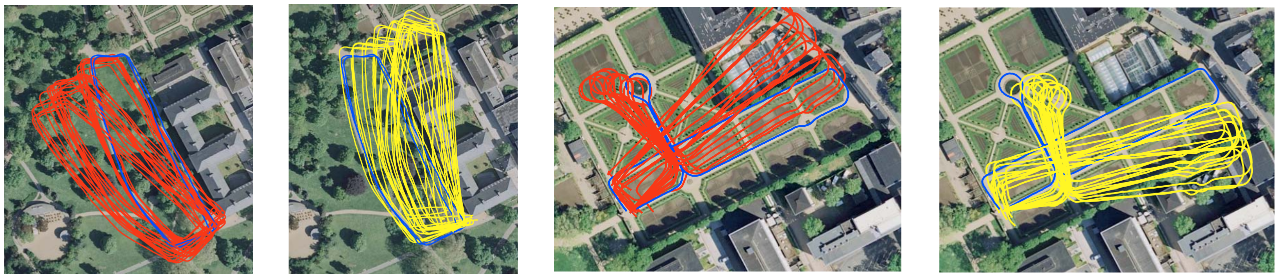
	deviation per stride(cm)			orientation error		
	median	$75\%^{ile}$	$95\%^{ile}$	median	$75\%^{ile}$	$95\%^{ile}$
Rotational	31.4	38.9	49.3	13.7	15.9	19.7
PCA2D	15.1	24.0	39.6	7.1	10.3	15.8
PCA2Df	**12.8**	**18.2**	**27.5**	**5.7**	**7.4**	**10.1**
PCA3Df	16.7	23.1	33.6	7.7	9.7	12.8
gyroPCA	47.6	58.2	77.2	21.0	24.4	32.6

Table I
OVERALL RESULTS PER METHOD, AVERAGED OVER BOTH POCKETS, TRACKS AND ALL 23 TRACES

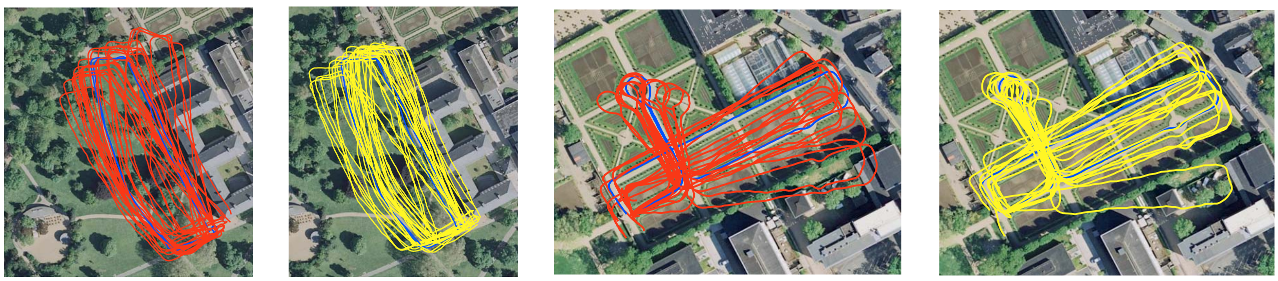
D. *Detailed Results.*

Fig.6(a) to Fig.6(e) show all resulting traces on the map per method, differentiated per pocket and track, with a ground truth trace given in blue.

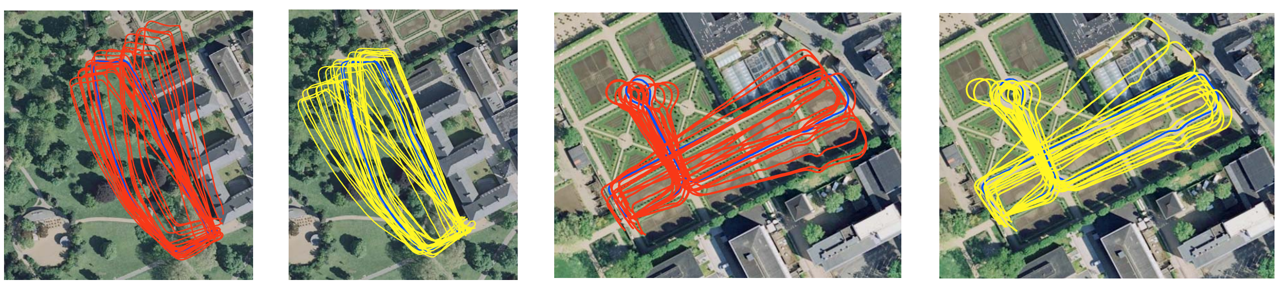
Fig.7(a) to Fig.7(e) show the corresponding deviation per step and directional error in terms of median, $25\%^{ile}$, $75\%^{ile}$ and $95\%^{ile}$ for all traces separately. Left and right pocket are given in separate plots, and the results are grouped within the plots by subject, with Park track given first for each



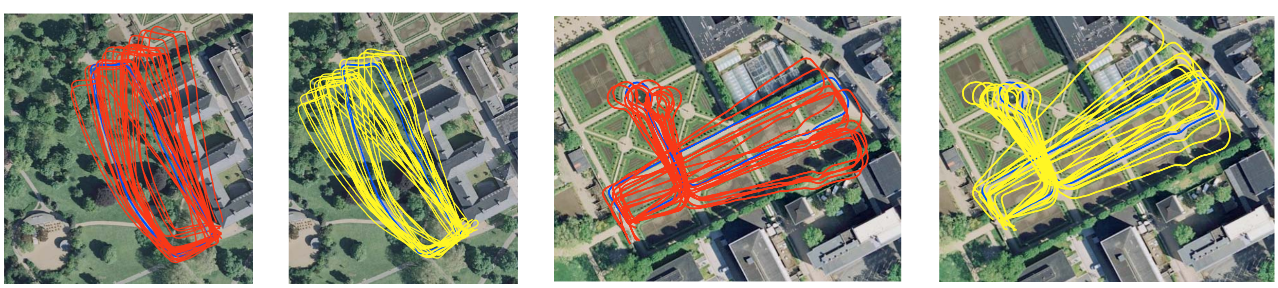
(a) Results for Rotational method



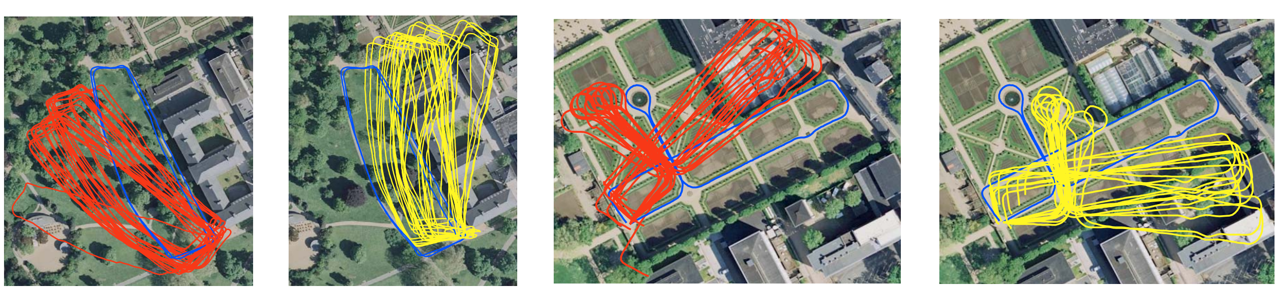
(b) Results for PCA2D



(c) Results for PCA2Df

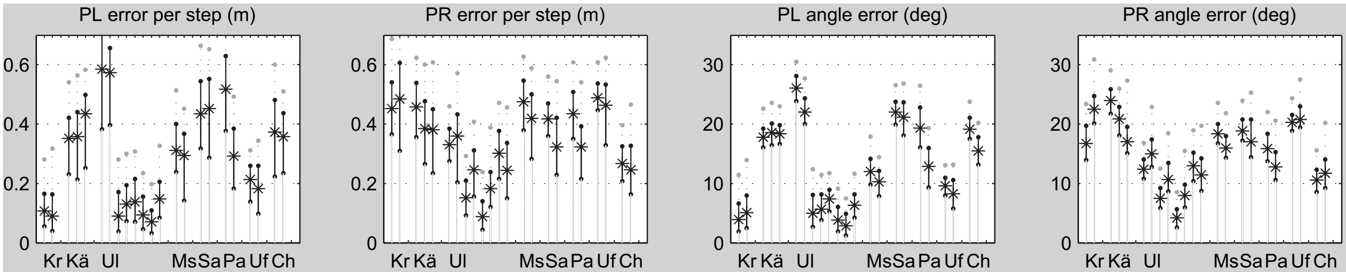


(d) Results for PCA3Df

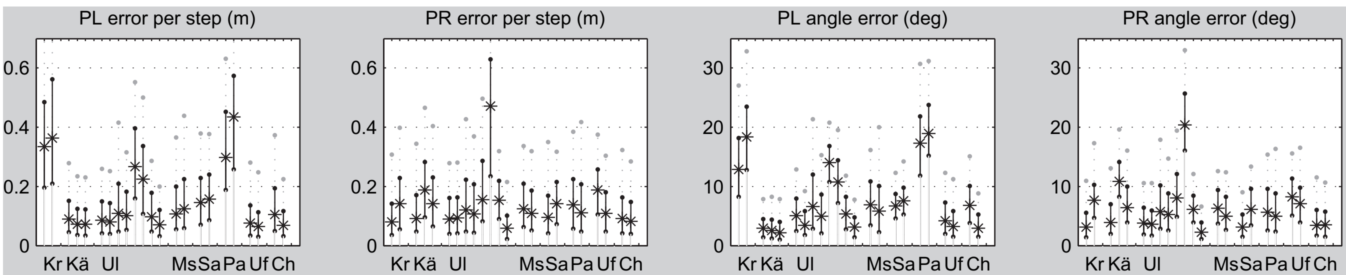


(e) Results for gyroPCA

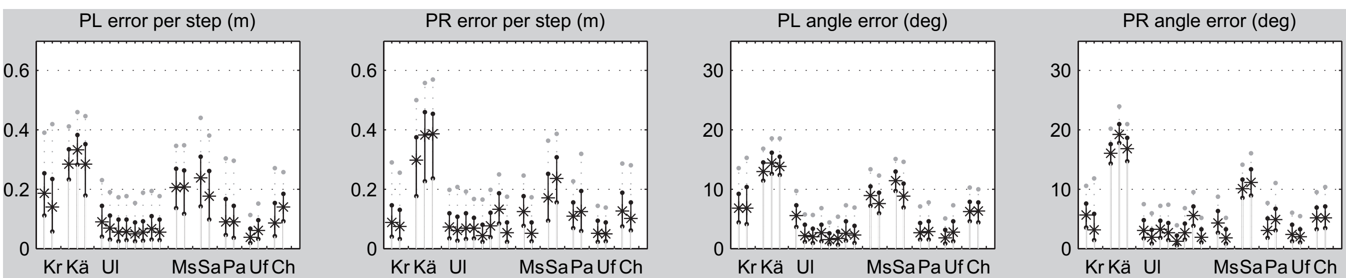
Figure 6. Resulting traces on map for all methods, separated per pocket and track. Park track on the left half (start in lower right corner, walked anticlockwise, then clockwise contiguously, 870m) and Garden (start in lower left corner, 415m) track on the right half; left pocket's traces of are red, right pocket's are yellow and ground truth is blue.



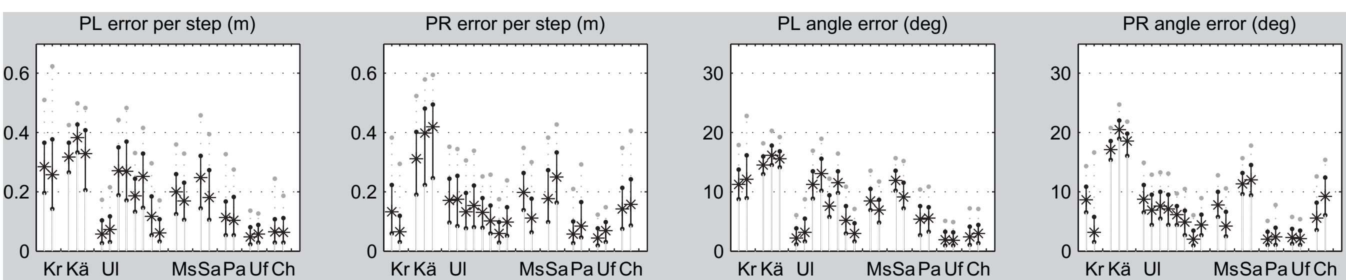
(a) Rotational method



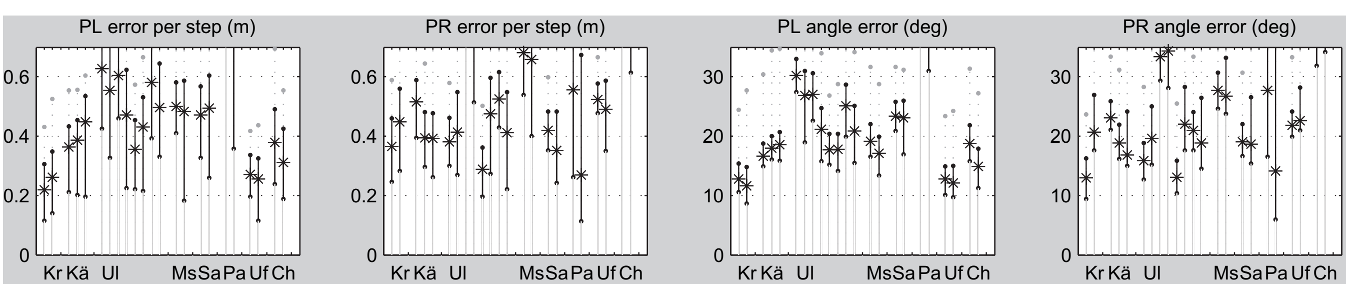
(b) PCA2D



(c) PCA2Df



(d) PCA3Df



(e) gyroPCA

Figure 7. Deviations per stride (heel-down to heel down of same foot, avg. 1.59m length) and directional errors for the different methods on the separate traces, each for left pocket (PL) and right pocket (PR) sensor. Median (*) with 25/75 percentile (.) and 95 percentile (grey .) are given. Traces are grouped by subject within plots, with Park trace given left and Garden trace right. (Park/Garden alternating for subject Ul's four different trousers)

subject, then Garden (alternating for subject Ul's different trousers).

1) Rotational: As one can see easily for the rotational feature in Fig.7(a), the results dependent on the pocket holding the sensor, and deviate to the left or to the right respectively. While the orientation offset within a trace is stable – as we see from the small intervals between $25\%^{ile}$ $75\%^{ile}$ – the amount of offset appears trouser dependent and hard to predict. As the directional offset is relatively stable, a correction by combination with GPS or map knowledge looks feasible in further work. Significant differences between left and right pocket of the same trousers instead of symmetric error with same amount, e.g., for Kr and U4, suggest that actual position in the pocket also influences the offset.

2) gyroPCA: Compared to the above method, the PCA analysis of gyroscope data to employ the rotational movement of the sensor, as proposed in [6], results in larger variance and larger offset for nearly all of the traces. While the approach has been successfully applied to find transitions between indoor-places it appears less suited for dead reckoning.

3) PCA2D: For many traces this method shows a higher variance in the directional error than the rotation based method, but gains a considerably lower directional offset in the traces. For Subjects Kr, Ul4 and Pa we encounter high offset and even instabilities in orientation estimates. (as visible, e.g., for rightmost traces for left pocket in Park in Fig.6(b)). We assume this is due to disturbing higher frequency agitations in these pockets due to foot impact, which are contained in the acceleration signal.

4) PCA2Df: Additional low pass filtering of the acceleration data with a moving average filter (5Hz) results in an overall lower level of directional offset, and lowest variance of error for all methods. While most trousers, and especially the outliers in PCA2D, benefit from noise filtering, we see an obvious rise of error for the Subjects Sa and Kä which wear tight trousers. This effect was visible also for other thresholds of the lowpass filter, increasing with lower cutoff. Thus we conclude that tight contact to the body leads to a shift of the significant motions to higher frequencies.

Considering only traces of normal and loose trousers, we obtain an average error as low as of 3.7° (5.4°/8.1°) for median ($75\%^{ile}$/$95\%^{ile}$) error, resulting in an average deviation from ground truth of 8.8cm (13.8cm/22.9cm). This corresponds to a 5.5% (8.7%/14.4%) deviation of distance traveled. Here it is important to note that this approach therefore has the same order of accuracy than our ground truth method and specifications given for commercial devices. This is interesting and highly encouraging as this result is obtained without any manually calibrated body offset and tedious requirement for stable fixation on the body.

5) PCA3Df: Applying PCA on 3 dimensional acceleration data with subsequent projection of the eigenvector to the horizontal plane turned out to be unstable. More specifically the extraction of the first or second eigenvector varied largely in terms of vertical orientation, due to generally high variance in sagittal plane. Employing the 3rd eigenvector, which is orthogonal to the plane of highest variance extracted by the first two eigenvectors, and application of low pass filtering to the acceleration signal allowed to extract the users orientation also with this approach. However, the resulting error is clearly higher than the previous 2-dimensional method. While variance of the directional error within traces are comparable to PCA2Df, the directional offset increased for most traces, with a tendency to the right side for the left pocket (and vice versa). The effect that tight trousers lead to lower accuracies due to low pass filtering is also noticeable in this method.

E. Discussion.

The strong correlation between directional error and resulting deviation per step leading for all results suggests that it is dominating source of error. Nevertheless, the error can be also influenced by mis-detected steps or incorrect estimates of the forward direction, lag in direction estimation in narrow turns and variations in step length within a trace.

As we used a fixed step length per trace, determined offline after recording and common for left and right pocket, the variance in the user's step length also contributes to the error.

As far as our step detection is concerned, we determined a high accuracy better than 1% error in step count comparing the pocket sensors to the dorsally mounted ground truth sensor. Also forward detection is working reliably, with only single errors on few traces.

It is hard to determine and single out these influences, as the accuracy of the best methods are already in the same order of accuracy as our ground truth (and even the specified accuracy of the XSens MTx sensors with 2° RMS orientation error). Even employing a dynamic step length estimation, our dead reckoning approach for ground truth is inherently exhibiting deviations from true position, and especially limited in directional accuracy by the stability of fixation to the body and errors due to magnetic deviations.

Surprisingly, the best results are gained from normal and loose trousers, and not the tight ones, which assure good contact of the sensor to the body. For consistently good results we would consider a special handling for tighter trousers, which do not benefit from lowpass filtering of the acceleration signal in the PCA2Df approach.

In summary, we conclude that we have successfully shown the feasibility of dead reckoning with a sensor placed freely in the pocket, and that the best methods can reach the same or better levels of accuracy as other dead reckoning approaches. This holds especially true for an everyday scenario where for a dorsally mounted sensor a stable fixation is hard to assure and rarely accepted by users; in our experience deviations of over 10 degrees can be expected due to shifting of the sensor when worn for longer periods.

V. Conclusion & Outlook

This work shows the promise of dead reckoning using solely a device placed freely in a trousers' front pocket. We analyzed for a mobile phone-shaped device several approaches to obtain a motion direction of the user, and combined it with reliable step detection and forward estimation to a full dead reckoning solution. In order to investigate whether a pocket dead reckoning approach can be largely robust of different users, trousers' pocket properties and actual sensor position, we evaluated all approaches on a large dataset of 23 traces, encompassing 11 different trousers, 8 subjects and 30km total distance.

The best PCA based approach shows a surprisingly low level of error and very consistent results for all normal and loose trousers, as good or even better than what we can expect from a body-affixed sensor, which is in real life scenarios subject to shift. The rotational approach – only employing the rotation of the sensor as input – shows a hard to predict body offset influenced by factors such as pockets shape and sensor position within. Nevertheless it would be also usable due to low variance of deviation within the track, if either the offset is corrected, e.g., by GPS or map/floorplan, or if the aim is to recognize traces by shape.

As promising directions for future research we see an extension to mixed indoor/outdoor scenarios and real-live long term recordings, also in combination with activity recognition. To counteract the accumulating error and higher disturbances in such scenarios, a combination with other (absolute) position methods (e.g., Wifi and GPS) and map matching appears to be very beneficial.

Furthermore, encouraged by the good results for the trousers' pocket, we see as an interesting question whether, and to which accuracy, also other typical phone positions allow for a dead reckoning approach, e.g., for hand bag, backpack, belt or shirt-/jacket pockets placement.

Lastly, for possible application on todays' mobile devices, we would need to examine a reduction of sensor requirements, as we currently rely on an orientation estimation derived from accelerometer, gyroscope and magnetometer with comparatively high accuracy.

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