Sensing Location in the Pocket

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ABSTRACT
We present an approach for recognizing location transitions of persons in buildings, using inertial sensor data from mobile devices. By normalizing trajectories using principal component analysis (PCA), our approach is robust to changes in sensor placement and orientation. On a data set containing 10 location transitions and 7 different placements/orientations of the mobile device, we achieve classification rates of about 95% in average. Moreover, when used in an online mode, we can predict the target location of the user with 80% certainty after the user has covered 35% of the path distance, on average.

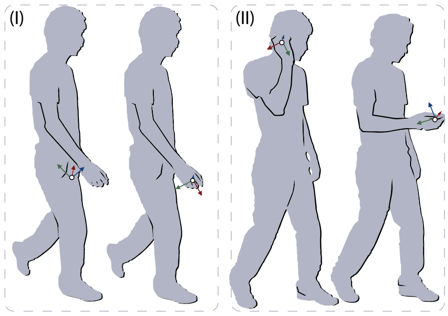

Figure 1. Different modes of carrying: *(i)* In the pocket, *(ii)* In the hand and during usage *(iii)* Talking, *(iv)* Typing a message, (left to right)

INTRODUCTION
Location awareness has gained a lot of interest for more than a decade now. Different kinds of wearable sensors, e.g., vision cues, proximity sensors, compass sensor, motion sensors, like gyroscopes and accelerometers, are used to estimate location or to classify location transitions [1, 2, 3, 4]. However one major drawback is the prior constraint of a careful placement of the device on the human body. This is generally hard to achieve in a real world scenario with inexperienced users.
The second drawback is that the position of the sensor is not assumed to be consistent with the position of a device which people already carry - their mobile phone.
A study revealed that around 60% of male owners of a mobile carry it in the trousers' pocket [5]. Thus, we mainly focus on carriage in the pocket. Whereas others try to predict where the sensor is located and how it is oriented [6, 7], our goal is to recognize location transition, which is robust against placement and orientation.
Modes of Carrying. Carrying a phone involves different possibilities of placements, either during interaction or merely during carriage. In turn, different placements have different characteristics. We focus on four which are, *(i) In the pocket (ii) In the hand*, *(iii) Talking* and *(iv) Typing a message*. We can assign these to two groups, *(I)* either the phone is carried (*i* or *ii*) or *(II)* it is being used (*iii* or *iv*).
Location Transition. A *location transition* is a sequence of locations visited by a user, starting at location A and ending at location B, with possible intermediate locations C, D, E, etc. Examples of locations are the user's office, the washroom, the printer room, etc.

ALGORITHM SKETCH
Our approach consists of two steps. First, we transform and normalize the recorded sensor data. The result is a trajectory in 2D space (Fig. 3). Second, we classify the trajectory into one of several possible location transitions. In the following we describe the two steps of the algorithm in more detail.
For *(I)* we propose an algorithm using body motion as a cue of the sensor's orientation. This way we are able to determine the relative orientation of the sensor to the body. We recalibrate continuously by a sliding window of 1 second to cope with orientation changes during operation. First trials showed that the window of $1s$ is sufficient to determine the main rotational component of the hip. Given global orientation and gyroscope values we perform the following steps for each timestamp t:

(1) PCA of 3D-gyroscope values over a $1s$-window
(2) Select first Eigenvector as axis $\omega(t)$ (Fig. 2)
(3) Project $\omega(t)$ onto ground plane
(4) calculate angle α between $\omega(t)$and $\omega(t-1)$ and create normalized heading vector

As for the hip, this works analogous for the hand. During phone usage *(II)*, we fixed the relative orientation to the body as the sensor is assumed to remain relatively steady. As output, we get a sequence of headings and the trajectories respectively (Fig. 4). The speed is assumed to be constant.
For the classification step we use a k-nearest-neighbor classifier on a correlation-distance measure, which is implemented to be rotation invariant. This results in the classified location transition.

EXPERIMENTAL SETUP
To evaluate our approach we recorded separately different location transitions at different sensor placements from a single user (see Fig. 1 for the placements and Fig. 4 for the recordings).

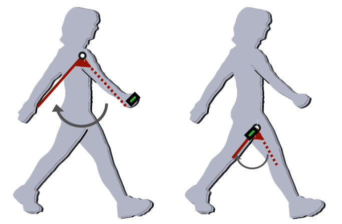

Figure 2. The rotational component during walking, the phone either carried in the hand (left) or in the pocket (right). PCA on 3D-gyroscope values gives us this axis in 3D-space.

Hardware. We use the IMU-system Xsens which provides inertial sensor data. Moreover, it fuses different modalities and provides a 3D-orientation estimate. We recorded the data at $100hz$ to a sub-notebook.

Dataset. For the evaluation we select 10 transitions between typical office locations (Fig. 3). For each transition we used *(i)-(iv)* as sensor placement. For *(i)* we used 4 different orientations. In total we recorded 70 sets.

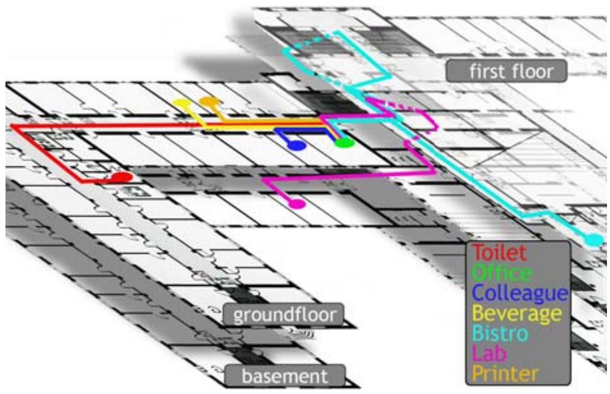

Figure 3. The location transitions recorded for our experiments. All transitions consist of the user walking either from his office to one of the locations (e.g. office-toilet) or back (e.g. toilet-office). The transitions for *beverage* and *printer* have the user's office as start and end location (e.g. office-beverage-office).

RESULTS

Our approach yields an overall recall and precision of 95% and 94%. In Fig. 4 we can see the trajectories created by the algorithm. While the overall results are good, one can observe that some trajectories are erroneous, e.g. *going to the printer*, while carrying the phone in the *hand*. This is the result of turning without walking where the rotational component of the hip is insufficient to determine the sensor's orientation and therewith the user's heading.

Additionally, we evaluated the online performance of a location prediction by taking different amounts of the user's covered path. Fig. 5 shows the results. It can be seen that after 35% of the covered trajectory we can predict the destination at a precision and a recall of above 80%. The maximum is at 75% of the completed path yielding 97% recall and 96% precision.

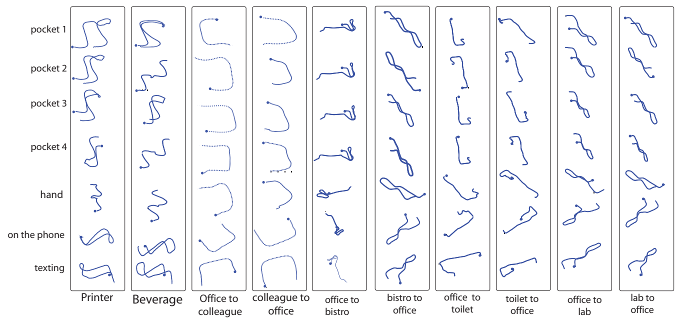

Figure 4. Resulting trajectories from classification. The columns indicate different location transitions, the rows the different sensor placements. For the pocket we used different orientations.

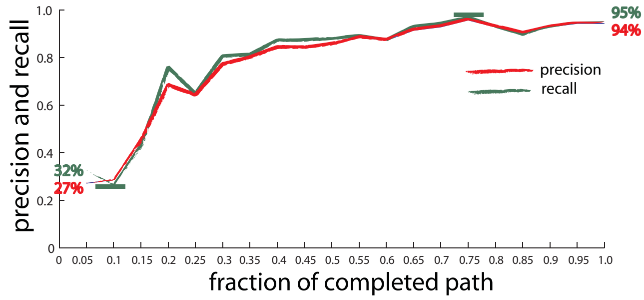

Figure 5. Using different fractions of the user's path.

CONCLUSION

We showed that it is possible to determine transitions between significant locations in an office scenario regardless of the placement and orientation of the sensor in a large extent. Based on our approach we were able to recognize these with a fairly high precision and recall rate of 94% respectively 95%. This preliminary result marks the first step toward online transition recognition on continuous data. Another planned improvement is to make the algorithm invariant to switches between the different modes of carriage during operation.

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