On-Body Smartphone Position Detection with Position Transition Correction Based on the Hand State

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Abstract. Smartphone users tend to store their devices at manifold on-body positions: in their trouser pocket, in their backpack, on the table, or simply in their hands. Depending on the position, it might be required to adapt the ringtone and notification type to enhance their perception. To do so, the smartphone needs to be able to automatically detect the device's position.

In this paper, we present an approach to detect the on-body position of the smartphone based on the smartphone features such as accelerometer data. In addition, we propose a position transition correction (PTC) algorithm to improve the position detection. The PTC assumes that each position transition involves the position "hand" as the user has to hold the phone into their hands to take them out of one position and place them another.

We gathered data from 20 participants and ran different classification methods. The KStar classifier achieved an accuracy of 81.97%. By applying the PTC we were able to correct about 50% of the errors on a simulated transition sequence, leading to an accuracy of almost 90%.

1 Introduction

By now, smartphones became an essential part of our everyday lives. They support us, but they can also be a burden by exposing us to an information overflow and to persistent availability. Different works already mention the importance of the smartphone position, e.g. for choosing an appropriate notification modality [3,4]. However, automatically inferring the on-body smartphone position is not an easy task. Different researchers already addressed this issue, e.g., [1,4–9]. Using common classifiers, we show that predicting the on-body position is possible with acceptable accuracy of up to 81.97%. To improve the accuracy, we introduce a position transition correction (PTC). We assume that each position transition has to involve the "hand" state: to take the smartphone out of the trouser pocket and into the backpack, it is necessary to pick up the phone, hold it in the hand and move it by hand from one position to the next one. Hence, we further assume that an apparent transition that did not include a hand state

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might be an error and not an actual position transition. Our correction mechanism builds up upon these assumptions and corrects the prediction results – leading to an increase of the accuracy and a decrease in errors.

2 Related Work

Smartphone position detection was investigated in different ways before. Some researchers started by recognizing the user's activity. Kunze et al. [6] first identified a walking activity before identifying the device position. They claimed that, while walking, certain movement patterns manifest themselves which help to classify the positions head, breast, and wrist. They applied a majority voting on the walking sequence and achieved a recognition accuracy of up to 100%. Vahdatpour et al. [8] also relied on a two step approach. First, they identified walking sequences using unsupervised activity discovery. Next, they used support vector machines (SVM) to classify the on-body regions lower arm, upper arm, and head. Using a model trained on 500 randomly drawn samples from a dataset with 2500 entries, they achieved an accuracy of 89%.

Alanezi and Mishra [1] go one step further. They also start by running an activity recognition. However, they do not limit themselves to the walking activity, but follow different classification strategies based on the recognized activity. They present a design for a recognition system and a first prototype.

There is also related work that does not rely on a former activity recognition but directly classifies the position. Kunze and Lukowicz [5] classified positions during different everyday activities. Using a hidden markov model (HMM) and a window size of 6 min, they achieved an accuracy of 82%. After merging front and back trouser pocket into one class, the accuracy rose up to 92%. Shi et al. [7] combine measurements from accelerometer and gyroscope to estimate the rotation radius. Afterwards, they calculate features based on the rotation radius and the angular velocity. They considered the positions chest pocket, trouser pocket, belt bag, and hand. A five-fold cross-validation using a SVM achieved an accuracy of 91.69%. Wiese et al. [9] relied on accelerometer data to detect smartphone positions and investigated the usefulness of other sensors. The accelerometer data alone yieled an accuracy of 79%. By including further sensors such as proximity sensor and ambient light sensor they pushed the accuracy up to 85%. Fujinami [4] investigated smartphone position detection based on the accelerometer only and yielded an accuracy of up to 80.1% for nine different position classes (around the neck (hanging), chest pocket, jacket pocket (side), front pocket of trousers, back pocket of trousers, backpack, handbag, messenger bag, and shoulder bag) and 85.9% for five different position classes (merging the four types of bags into one class and the two trouser pockets into one class).

It seems promising to rely on smartphone features, especially accelerometer data. Some researchers already considered the hand position. Antos et al. even mentioned the meaningfulness of a hand state as transition between different positions [2]. We will combine these ideas and present a smartphone features-based position recognition and a position transition correction based on the hand state.

3 Common Smartphone Positions

To assess where users store their smartphone commonly and which positions we should consider in our specific investigations, we ran a short online survey. Overall, 76 persons participated, aged between 17 and 36. We asked them with which frequency they store their phone in a specific position: trouser pocket, backpack, jacket pocket, purse, shirt pocket, wristband, belt bag, back pocket, on the table, or in the hand. The results are depicted in Table 1. Based on these results, we decided to consider the following positions: trouser pocket, hand, backpack, purse, and on the table.

Table 1. Results of the online survey to assess most common smartphone positions over all activities (sit, stand, walk, jog, ride a bicycle) in %.

Position	Frequency
Trouser pocket	53.22
Hand	37.40
Backpack	31.62
Jacket pocket	24.44
Purse	23.11
Table	21.71
Shirt pocket	5.26
Wrist	2.11
Belt bag	0.64
Back pocket	0.26

4 Predicting the Smartphone Position

4.1 Data Assessment and Feature Selection

We wrote an Android application to assess smartphone data. We considered features derived from data gathered using the accelerometer, gyroscope, proximity sensor, light sensor, and screen activity. Data was downsampled to 30 Hz and partly transformed using Fast Fourier Transformation (FTT). We investigated different windowing schemes and chose a step size of 120 and an overlap of 60 as it yielded the best results.

We considered the following features: average per frame, average of the FFT bin, FFT max bin index, DDT sum of the first/second/third/fourth quarter, highest/lowest/last value of the frame, first/third quantile, root mean square, standard deviation, sum of all values, squared sum, variance, and number of zero crossings. This leads to a total number of 198 features (11 sensor measurements * 18 features). To reduce the number of features for the final classification, we ran different feature evaluation mechanisms, namely: SymmetricalUncertAttributeEval, ReliefFAttributeEval, OneRAttributeEval, CorrelationAttributeEval, InfoGainAttributeEval and GainRatioAttributeEval. In each case, the features derived from the accelerometer measurements yielded the best results.

4.2 Study Design and Sample Description

We collected data from 20 subjects (6 female, 14 male) in-field. We asked the participants to perform at least the activities sit, stand, and walk, and optionally to jog or ride a bicycle. During each activity, the phone was stored at each considered smartphone position – excluding the combination hand and bicycle due to security concerns. For each combination of subject, activity, and position we collected one minute of data.

4.3 Classification

As mentioned above, we preprocessed the data and ran a feature selection to identify the best features. Using these features, we trained different classifiers provided by WEKA[1], namely a support vector machine (LibSVM), two tree-based methods (RandomForest and RandomTree) and two instance-based approaches (KStar and IBk). We decided to use leave-one-person-out cross-validation. The accuracies per classifier are shown in Table 2. The highest accuracy of 81.97% was achieved by the KStar classifier.

Table 2. Accuracy for recognizing smartphone positions per classifier in %.

Classifier	LibSVM	RandomForest	RandomTree	KStar	IBk
Accuracy	81.29	81.01	77.24	81.97	81.73

5 Position Transition Correction (PTC)

5.1 PTC Theory

Antos et al. [2] already labeled the state during a position transition as *hand*: their subjects used their hands to change the device's position. We assume that every significant position transition is realized using the hand. This assumption can be illustrated by the following example: a user takes the smartphone out of their trouser pocket (p_0) using their hand (h) and places it in their shirt pocket (p_1):

$$TrouserPocket\ (p_0) \rightarrow Hand(h) \rightarrow ShirtPocket(p_1)$$

Consider the following, exemplary classification result:

$$TrouserPocket\ (p_0) \rightarrow ShirtPocket\ (p_1) \rightarrow TrouserPocket\ (p_0)$$

If we assume that a hand position has to appear in between any other two positions then this example must be a recognition error. Either, the hand state was missed, it was misinterpreted as a shirt pocket, or the device stayed in the

[1] https://www.cs.waikato.ac.nz/ml/weka/.

trouser pocket the whole time and was wrongly recognized as being in the shirt pocket.

Our TCP mechanism would inspect every window of data within the sequence. First, we look for each hand transition in the sequence. Next, we perform a majority voting on the transitions in between to decide in which position the smartphone is during that subsequence. An example for a successful correction is visualized in Fig. 1.

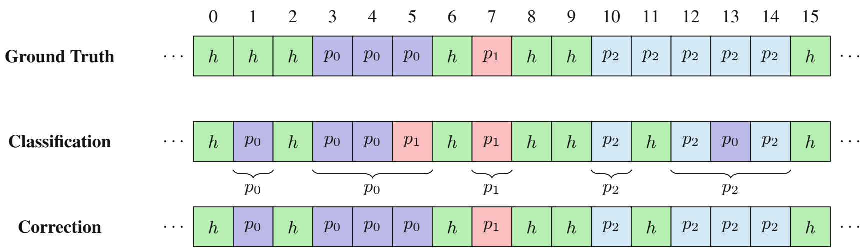

Fig. 1. A sequence correction that successfully reduced the number of errors.

5.2 PTC Evaluation

As input we use a simulated sequence. The sequence was created from ground truth data and transformed by using probabilities taken from the confusion matrix of the classifier results we gained from the leave-one-person-out cross-validation.

To rate the PTC, we compare the ground truth information with the PTC-corrected version of the simulated sequence. Thanks to the PTC almost 50% of all errors could be reduced and the accuracy was increased to about 90%. However, we have to note that a good detection of the hand position is essential for the correct functioning of the PTC.

6 Conclusion

This paper focused on predicting the smartphone position based on smartphone features while the phone is stored at different positions during different everyday activities.

First, we ran an only survey to assess common smartphone positions for common activities such as sit, stand, walk, jog, and ride a bicycle. We identified hand, trouser pocket, backpack, purse, and on the table as positions.

We collected data from 20 participants while they underwent different everyday activities and stored the smartphone at different positions. Concerning sensors, we considered accelerometer, gyroscope, proximity sensor, ambient light sensor, and screen activity. After running different feature selection algorithms provided by WEKA, we decided to focus on accelerometer data only. We only relied on the sensor measurements and did not run an activity recognition first. Using common classifiers, again provided by WEKA, we achieved recognition accuracies of up to 81.97%. The results have to be treated with care as we only had a limited amount of data. However, we required a confusion matrix to simulate a position transition sequence. For this use case, the amount of data was sufficient.

We also proposed a position transition correction (PTC). The PTC mechanism assumes that each position change has to include a hand transition. Applied to a simulated sequence of position changes, the PTC reduced the errors by about 50% and improved the recognition accuracy to about 90%. We propose to enhance the PTC by introducing a minimum duration for hand transitions or to combine it with other correction methods.

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