Recognizing a Mobile Phone's Storing Position as a Context of a Device and a User

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Abstract. A mobile phone is getting smarter by employing a sensor and awareness of various contexts about a user and the terminal itself. In this paper, we deal with 9 storing positions of a smartphone on the body as a context of a device itself and a user: 1) around the neck (hanging), 2) chest pocket, 3) jacket pocket (side), 4) front pocket of trousers, 5) back pocket of trousers, 6) backpack, 7) handbag, 8) messenger bag, and 9) shoulder bag. We propose a method of recognizing the 9 positions by machine learning algorithms with 60 features that characterize specific movements of a terminal at the position during walking. The result of offline experiment showed that an overall accuracy was 74.6% in a strict condition of *Leave-One-Subject-Out* (LOSO) test, where a support vector machine (SVM) classifier was trained with dataset from other subjects.

1 Introduction

A mobile phone terminal is getting smarter due to the advancement of technologies such as Micro Electro Mechanical Systems (MEMS), high performance and low power computation. Various sensors are embedded into or attached to a mobile phone terminal and a wide variety of contextual information can be extracted, which is about a user, a device and/or environment. These sensors are (or will) not only utilized for explicit usage of the terminal's functionalities like user authentication [17], display orientation change and backlight intensity control [7], but also for activitiy recognition [18], indoor location [2], the state of a device [8], pedestrian identification [21], environment [20], etc. In this paper, we focus on the position of a smartphone on the human body as a context. The position is not an exact 3D coordinate, but parts of our body or clothes such as "hanging from the neck" and "inside a chest pocket".

According to a study of phone carrying, 17% of people determine the position of storing a smartphone based on *contextual restrictions*, e.g. no pocket in the T-shirt, too large phone size for a pants pocket, comfort for an ongoing activity [5]. These factors are variable throughout the day, and thus smartphone users change their positions in a day. This suggests that a context, *on-body placement*, has great potentials in improving the usability of a terminal and the quality of

K. Zheng, M. Li, and H. Jiang (Eds.): MOBIQUITOUS 2012, LNICST 120, pp. 76–88, 2013.

sensor-dependent services, facilitating human-human communication, and the reduction of unnecessary energy consumption.

On-body position sensing is getting attention to researchers in machine learning and ubiquitous computing communities [6][19][22], which starts from the work of Kunze et al. [11]. Vahdatpour et al. recently proposed a method to identify 6 regions on the body, e.g. head, upper arm, for health and medical monitoring systems [22]. In their case, a sensor was attached directly on the skin or on the clothes, and the recognition process were conducted in an offline manner. A preliminary work by Shi et al. seeks a method of on-body positioning of a mobile device into typical *containers* such as a trousers' pocket. Inertial sensors, i.e. accelerometer and gyroscope, are utilized in these work. By contrast, Miluzzo et al. proposes a framework of recognizing the position of a mobile phone on the body using multiple sensors [15]. In their initial stage, a simple placement, i.e. inside or outside pocket, is subject to detect using an embedded microphone. In this paper, we deal with nine storing positions including bags. Recognizing a situation in which a terminal is in a bag is challenging because of the diverse shape of a container and the carrying style. We attempt to find a set of features that can characterize and discriminate the motion of a smartphone terminal in a periodic motion, e.g. walking, using an embedded accelerometer. To the best of our knowledge, this is the first attempt to recognize a wide variety of a bag as a storing position.

The rest of the paper is organized as follows: Section 2 describes our approach. The performance of the algorithm is evaluated in Section 3. Then, the results are analyzed in Section 4. Section 5 describes implementation on an Android platform as a shareable component. Possible application scenarios are presented in Section 6 with validation of the results. Finally, Section 7 concludes the paper with future work.

2 On-Body Placement Detection Method

We describe the approach of the placement-detection and recognition features.

2.1 Target Positions and Sensing Modality

Nine popular positions shown in Fig. 1 are selected as the targets of recognition: 1) around the neck (hanging), 2) chest pocket, 3) jacket pocket (side), 4) front pocket of trousers, 5) back pocket of trousers, 6) backpack, 7) handbag, 8) messenger bag, and 9) shoulder bag.

Including a *bag* as a storing position is technically challenging due to its diverse shape of a container, e.g. a side pocket, and carrying style; however, as the survey [5] shows, a bag is a major location for storing a mobile phone for especially women (about 60%), and about 50% of them do not notice incoming call/message in their bags, which motivated us to detect a situation of carrying a mobile phone in a bag. If a mobile phone knows that it is inside a bag, it may ring louder or respond to the caller that the callee may take some time to answer the call [7]. Although Kawahara et al. utilized a heuristic that the variance of acceleration signals in a certain window is nearly zero when a mobile phone is in a bag [10], it is obviously not applicable while a person is moving. The four types of bags were specified as popular ones based on a pilot study on the street. We determined to recognize these types separately, rather than handle as one single type *bag*. This is because the movement patterns that we utilize in recognizing a storing position are so different from each other. Note that the type of a bag is not determined by the name and the shape, but by the relationship with the body, as shown in Table 1. So, a mobile phone inside a "handbag" (upper-right corner of Fig. 1) that is being slung like a shoulder bag (lower-right corner) is classified into "shoulder bag".

We have adopted an accelerometer to obtain signals that can characterize movement patterns generated by dedicated storing positions while a person is in a periodic motion, e.g. walking. The utilization of an accelerometer makes the placement detection feasible on today's smartphones because of the popularity. A feature vector is obtained from three-axes accelerometer readings, and our system classifies it into one of the nine positions.

Fig. 1. Target Storing Positions

Table 1. Characteristics of the four types of bags

Type	Way of sling	Relationship with body
backpack	over both shoulders	on the back
handbag	holding with hand	in the hand
messenger bag	on the shoulder opposite to the bag	around the waist
shoulder bag	on the same side of the shoulder as the bag	side of the body

2.2 Storing Position Recognition Process

Fig. 2 illustrates a flow of data processing from sensor readings to an event of placement change. A data processing (recognition) window is generated every 8 samples, i.e. the length of sliding from raw acceleration signals sampled at 25Hz. The effect of the window size on the recognition performance is discussed later.

As described above, the recognition is carried out while a person is in a periodic motion, e.g. walking, in which specific periodic movement patterns of a phone terminal are subject to recognize. Non-periodic motions such as jumping and sitting can be included in a stream of acceleration signal. So, a period of *walking* needs to be determined prior to position recognition, which is based on the constancy of acceleration signal proposed in [16]. Note that a person may change the storing position of a phone terminal while she is standing still. An action of storing(removing) a mobile phone terminal into(from) a certain storage position, e.g. a chest pocket, is also considered as a non-periodic motion. In [6], we proposed a method to recognize a specific gesture for each position. In the future, the result of the constancy decision is utilized to call appropriate recognition process: periodic movement patterns or storing gestures.

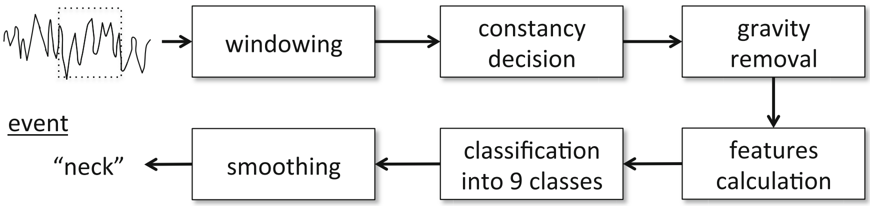

Fig. 2. Position Recognition Process

In the next stage, the acceleration of gravity is removed from the sensor readings and obtain force component for each axis. We adopted a method proposed by Cho et al. [4], in which the gravity components are approximately removed by subtracting the mean of accelerations at each time. Here, the mean is obtained per window. The approximate movement force is then normalized by the mean of the norm of three-axes components. A window of acceleration signal that is determined as what is obtained during walking in the previous stage is then given to a nine-class classifier. Since an output of the classifier is window-basis, *temporal smoothing* is carried out to reject a pulsed different output. Here, a majority voting is applied among successive 11 outputs. In this way, one position recognition is performed. In case of a change in the storing position, an event is generated so that an application could adapt to the change.

2.3 Recognition Features

Initially, we listed candidates of features by taking into account the independency on the direction of a terminal and the complexity of calculation, which was 130 features in total. Then, a machine learning-based feature selection (a forward searching) is applied to collected dataset using Weka [13]. Table 2 shows the selected 60 features for window size of 256. Note that x, y, and z axes of the accelerometer of NexusOne are set to the direction of *width*, *height* and *thickness* in a portrait mode, respectively.

Table 2. Selected Features (window size = 256; 60 features in total)

No.	Description	axis
1	S.D of amplitude	y, z
2	Max. amplitude of frequency spectrum	z
3	Frequency that gives the max. frequency amplitude	x, y
4	Max. of S.Ds of amplitude in frequency-windows (Max SDF)	y, z
5	Index in a frequency-window that gives the Max SDF	y
6	Max. amplitude in the low-frequency range	x, y, z
7	Max. amplitude in the mid-frequency range	y
8	Max. amplitude in the high-frequency range	y
9	S.D of amplitude in the mid-frequency range	y
10	S.D of amplitude in the high-frequency range	x, y
11	Min. amplitude of absolute value	x, y
12	Max. amplitude of absolute value	y, z
13	Inter-quartile range of amplitude in the time domain	z
14	Correlation coefficient between two axes	x-y, x-z
15	2nd max amplitude in the frequency domain	x, y, z
16	Frequency that gives the 2nd max amplitude	x, y
17	75 percentile of frequency amplitude	x, y, z
18	Inter-quartile range of amplitude in the frequency domain	y
19	Correlation coefficient in the entire frequency range	x-y, x-z, y-z
20	Correlation coefficient in the low-frequency range	x-y, x-z, y-z
21	Correlation coefficient in the mid-frequency range	x-y
22	FFT entropy in the entire range	x, y, z
23	FFT entropy in the low-range	x, y, z
24	FFT energy in the mid-range	x, y, z
25	FFT entropy in the mid-range	z
26	FFT energy in the high-range	x, y, z
27	Binned distribution of time domain values	x_2, x_6, x_9, y_4, y_9 z_4, z_5, z_6

S.D.: Standard Deviation, $axis_i$: i-th bin of binned distribution ($i = 1..10$)

The term “frequency-window” is a 2.93Hz window slid by 0.1Hz in frequency spectra. These window size and sliding-width were heuristically determined. The frequency spectra are divided into three “frequency ranges”, in which *low*, *medium*, and *high* correspond to 0-4.2Hz, 4.2-8.4Hz and 8.4-12.5Hz, respectively. The FFT energy is calculated as the sum of squared values of frequency components, which is normalized by dividing by the window size [1]. The FFT entropy is then calculated as the normalized information entropy of FFT component values of acceleration signals, which represents the distribution of frequency components in the frequency domain [1]. The Binned Distribution is defined as follows: 1) the *range* of values for each axis is determined by subtracting minimum value from maximum one; 2) the range is equally divided into 10 bins; and 3) the number of values that fell within each of the bins is counted [12].

3 Evaluation on the Basic Performance of the Classifier

We describe the experiments on the classifier from the aspects of 1) window size, 2) types of classifier, 3) generalization, and 4) specialization. Note that *smoothing* process is not applied to the decisions of the classifiers.

3.1 Data Collection

Data were collected from 20 graduate/undergraduate students (2 females). They were asked to walk about 5 minutes (30 seconds x 10 times) for each storing position. To collect data from naturalistic condition, we asked participants to walk as usual, and there was no special instruction about the orientation of the device. Also, they wore their own clothes; we only lent them clothes in case that they did not have clothes with pockets. As for bags, we utilized one particular bag for each type of the category of a bag, and we asked the participants to carry bags as designed. That is, for example, carrying handbag with one hand, not slinging over a shoulder like a "shoulder bag". Totally, we obtained about 150,000 samples per position.

3.2 Experiment 1: The Effect of Window Size and Classifiers

As a first step, we evaluated the effect of the window size for feature calculation and various classifiers. We tested with three classes of window size, i.e. 128, 256 and 512 (5.12, 10.24 and 20.48 seconds, respectively). The categories of classifiers that we compared with are 1) an ensemble leaning method (Random Subspace method [9]), 2) a decision tree method (J48), 3) a Bayes method (Naive Bayes), 4) a support vector machine (SVM) classifier and 5) an artificial neural network-based method (Multilayer Perceptron (MLP)). After recognition features were calculated for each window size and stored in text files, we ran 10-fold cross validation (CV) tests on the Weka machine learning toolkit[13].

Fig. 3 shows the relationship between the window size and the accuracy of 10-fold CV, in which SVM performed best with all size of the windows (98.6, 99.4 and 99.7 %, respectively). We determined to utilize the size of 256 for the upcoming experiments although the accuracies increase as the size of the window grows. This is because a window of 512 samples takes 20.48 seconds to be available, which indicates that a window is usable only if a person is walking for more than 20.48 seconds, otherwise a window might be rejected at the constancy decision phase or lead to incorrect recognition. Additionally, the accuracy is being saturated with the size of 256.

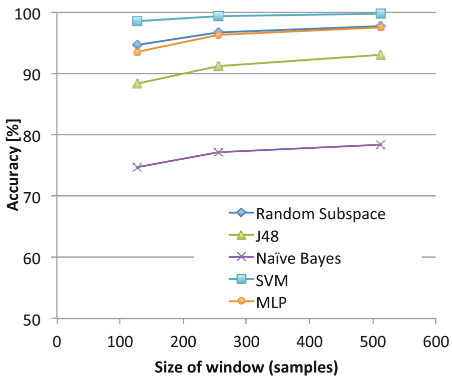

Fig. 3. Accuracy with different size of window and classifiers (10-folds CV)

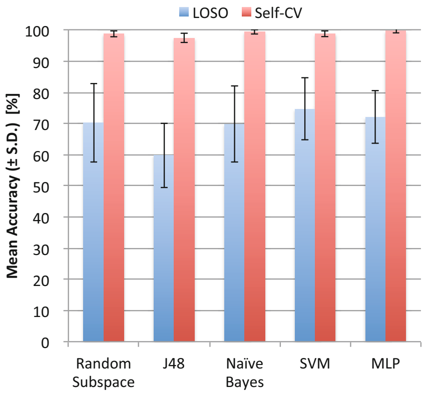

Fig. 4. Mean accuracy with different classifiers in LOSO and Self-CV test (window size = 256, average number of instances per person = 701)

3.3 Experiment 2: Leave-One-Subject-Out Test

To see the capability of the generalization of the recognition system, we carried out Leave-One-Subject-Out (LOSO) test with the same dataset as Experiment 1. In a LOSO test, dataset from one person is utilized as a test set, while the others are utilized as training sets. A LOSO test can measure the performance on a realistic situation such that a person purchases an on-body placement-aware functionality from a third-party, because the data from a particular person are not utilized to train a classifier. Here, we iterated one test process for all (20) the persons in the dataset and calculated statistics.

In Fig. 4, the mean accuracies for various classifiers is presented as the bar on the left. The accuracies degraded 8 (Naive Bayes) to 32 (J48) points from CV-test. SVM also performed best, where the mean, the lowest and the highest accuracy are 74.6 %, 55.9 % and 89.8 %, respectively.

3.4 Experiment 3: Self-Cross Validation Test

Finally, a self-cross validation (Self-CV) was carried out to investigate the capability of specialization. Here, a 10-folds CV was conducted with dataset obtained from a particular person. On the right bar in Fig. 4, the mean accuracies were presented. All the mean accuracies were more than 97.0 % with small standard deviations, in which MLP performed best (99.7 %).

4 Analysis

The 10-folds CV (experiment 1) showed high accuracy (99.4 % with SVM); however, the performance in the LOSO test (experiment 2) was degraded and diverse in individuals ranging from 55.9 % to 89.8 %. Table 3 shows an aggregated confusion matrix of the LOSO test, in which each person's confusion matrix was accumulated to see the overall mis-recognition.

The recognition of "neck" performed very well in both recall (97.3 %) and precision (94.2 %). We consider that the moving pattern of an object hanging from the neck is quite different from the others. This might be applicable for a class of applications that monitor environmental conditions such as temperature and humidity since the measurement from the neck often differs from trousers pockets due to the effect of body heat and sweat [24]. An application can take an appropriate action, e.g. correction to the value measured outside and alerting a user, when a monitoring device (smartphone) is inside a trousers' pocket.

The low recall (65.1%) and precision (57.0%) of the recognition of "jacket's pocket" was due to relatively high heterogeneity of the shape of the pocket. The mis-recognitions of "jacket's pocket" from "shoulder bag" (192), "chest pocket" (186) and "messenger bag" (157) are reasonable because the three positions also have the diversity compared to the other positions. Also, the carrying positions of "shoulder bag" and "messenger bag" are close to a "jacket's pocket", which generate similar movement patterns. The data that belong to "messenger bag" are often mis-classified into "trousers' back pocket" (187), "backpack" (160) and "jacket's pocket" (157). We consider that this is because "messenger bag", "backpack" and "jacket's pocket" have enough room to move around. Also, the relationships with the body are similar in "messenger bag", "trousers' pocket" and "backpack" as shown in Table 1.

Table 3. Aggregated Confusion Matrix of LOSO test

	1	2	3	4	5	6	7	8	9	Recall
1	1504	4	14	1	2	0	1	0	20	97.3%
2	4	1183	186	4	13	0	16	81	36	77.7%
3	53	143	985	39	24	53	21	66	129	65.1%
4	7	1	93	1042	156	0	13	181	35	68.2%
5	1	49	34	92	1311	0	4	57	20	83.6%
6	0	44	17	0	0	1281	118	41	74	81.3%
7	2	58	51	0	0	95	1304	0	76	82.2%
8	9	94	157	95	187	160	51	706	143	44.1%
9	17	13	192	1	2	10	140	37	1168	73.9%
Precision	94.2%	74.4%	57.0%	81.8%	77.3%	80.1%	78.2%	60.4%	68.7%	74.8%

Row: original class, Column: predicted class.
Class label: 1=neck ,2=chest, 3=jacket's pocket, 4=trousers' front pocket, 5=trousers' back pocket, 6=backpack, 7=handbag, 8=messenger bag, 9=shoulder bag

Table 4. Recall and Precision with Aggregated Positions

	1	2	3	4+5	6+7+8+9
Recall	97.3%	77.7%	65.1%	84.0%	87.8%
Precision	94.2%	74.4%	57.0%	93.6%	88.1%

Class labels are the same as in Table 3.

By taking into account the semantic similarity of trousers' front and back pockets, they can be merged into one class "trousers' pocket". Similarly, the four types of bags can be considered as "bag". Table 4 shows the recall and the precision of the merged classes, in which the new classes are recognized well.

The accuracies in Self-CV were high (more than 97.0 %) because the complexity in the operating environment decreases. Even the worst classifier in the LOSO test (J48) got the accuracy of 97.5 %. We consider that it is necessary to investigate not only *stronger* features or classifiers but also a mechanism to adjust to an individual user in a post hoc manner. This can be addressed by integrating a sophisticated HCI technique with a semi-supervised machine learning technique. The method should be designed to motivate a user to make a personal belongings smarter by herself, which we are currently under investigation.

5 Implementation

The storing position recognition should be provided as a shareable component to allow application developers to focus on the application logic development as well as to maintain the consistency of various applications' behavior. Thus, we have selected the Google's Android platform because it allows an application to run background. We developed a software framework to bridge the proposed functionality with user applications, which is realized by Android inter-process communication (IPC) framework and our original Java interfaces and classes.

A compact version of Weka [14] and a support vector machine library (LIBSVM [3]) are utilized to run a SVM model trained by Weka on a PC. The elapsed times of the feature calculation and the net classification on Samsung Galaxy Nexus platform (OS: Android 4.0.4, CPU: Texas Instruments OMAP4460 1.2GHz Dual Core, RAM: 1 GB) are about 100 msec and 7 msec, respectively. As described in Section 2.2, a window is generated every 8 samples (= 320 msec). So, we consider that the current processing speed is enough for completing one cycle of recognition until the next window creation.

6 Applications of On-Body Position Recognition

We discuss applications to emphasize the relevance of the placement-awareness of a mobile device, which is classified into three categories: smart notification, annotation for sensor readings and functionality control.

6.1 Smart Call/Message Notification

In our preliminary study, we found that the ease of perceiving an audio alarm and vibration of a mobile phone differs among the storing positions: "hanging from the neck" allowed notification with significantly smaller audio volume than the others. Moreover, "inside a chest pocket" and "hanging from the neck" were the fastest and the latest in the notification with the vibration, respectively [23].

This suggests that the notification should be adaptive to the storing position to save energy while allowing prompt and effective communication. The current high recognition performance of "hanging from the neck" might at least allow notification to a user with minimal audio volume when a terminal is there. Also, a caller can be notified of the possible delay in case a terminal is "not hanging from the neck", which is suggested by Cui et al. [5] and Gellersen et al. [7] to make communication smoother.

6.2 Assuring Sensor-Dependent System's Behavior

A sensor-augmented mobile phone is suitable for recognizing activity and physiological states of a user as well as monitoring environmental states around her in an implicit and continuous manner [12,15]. An issue is that people may change the storing position for some reasons as described before. This implies that an application would not perform as designed if the prerequisite is not upheld. We propose to utilize the storing position as *meta-data* that are attached to primary information processed by an application to assure reliable application's behavior.

In the activity recognition using wearable sensors, the sensors are basically assumed to be at an intended position [1,18]. In [18], an accelerometer hanging from the neck contributed to capture certain kind of movement of the upper body. In this case, our method can ask a user to keep hanging a mobile phone from the neck or turn the sensing component off to avoid noisy measurement based on application requirements.

In the paradigm of human-centric sensing, where a sensor-augmented mobile phone is utilized to capture environmental information throughout daily lives, the storing position of a mobile phone terminal is considered as a key element of reliable measurement because the measurements is affected by storing positions [15,20], especially "outside a container". We actually found a difference in the readings from a relative humidity sensor and a thermometer due to the effect of body heat propagation [24]. The fact not only has an impact on the correctness of environmental data collection, but also on the estimation of a risk from an environmental state such as heatstroke and influenza. The correctness of the risk estimation relates to the physiological condition of a user and the trust of a user on the device due to under- and over-estimation, respectively. We have developed a placement-aware heatstroke alert device that provides a message of possible under- (over-) estimate of the estimated risk level based on the relationship between the data from outside, i.e. "hanging from neck", and that of other positions [24]. We consider that the aggregated performance (Table 4) is promising for this application.

6.3 On-Body Placement-Aware Functionality Control

A mobile phone can control its functionality based on the placement. Harrison et al. specify a couple of application in this category: screen component would be switched off when a mobile phone is not visible, and keypads would be locked to avoid accidental input, e.g. in a pocket with keys [8]. These applications just like to know if a device is inside a storage container such as a pocket and a bag, which is not hanging from the neck (=outside) in our system's sense. As shown in Table 3, both the recall and the precision of "neck" are high (97.3 % and 94.2 %, respectively), which makes the scenario practical with our system.

In terms of functionality controlling for energy saving of a device itself, a mechanism of handling inaccurate placement of a mobile phone, *suspending*, can be classified into this category; an application would turn itself off to save energy after alerting to a user for a while without response from her.

7 Conclusion and Future Work

In this paper, we proposed a method to recognize a storing position of a mobile phone while it is being carried. To recognize nine positions, we specified sixty features obtained from a 3-axes accelerometer. The processing window size of 256 were chosen by taking into account the continuity of motion, i.e. walking, as well as the accuracy of recognition. Five types of classifiers were tested.

The results of offline experiment showed that an overall accuracy of identifying the nine positions with SVM classifier was 74.6% in a strict condition of LOSO test, which was the best in the other classifiers. Aggregations of positions (trousers' pockets and bags) showed better and promising performance in recall and precision. The results of Self-CV showed almost perfect recognition performance, which implies the necessity of on-the-fly or post-hoc personalization of a classifier for practical use. The proposed method was implemented on an Android platform as a shareable service, and we confirmed that one cycle of recognition finishes within sliding interval (320 msec).

We will incorporate a method of detecting the change of a storing position while a person is not walking, which is under investigation, in order to keep track of the position of a mobile phone all the time. Currently, the recognition process is repeated every 320 msec, which we consider can be optimized by changing the duty cycle while taking into account the delay to wake-up acceptable for an application. An application case study with a heatstroke alert is also planned to have deep understanding of the new idea of on-body placement-awareness of a smartphone from the perspective of human-sensor interaction.

Acknowledgments. This work was supported by MEXT Grants-in-Aid for Scientific Research (A) No. 23240014 and Kayamori Foundation of Information Science Advancement.

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