Surrounding Context and Episode Awareness using Dynamic Bluetooth Data

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ABSTRACT

Bluetooth information can efficiently capture characteristics of user-centric surrounding contexts, such as formal meeting or chatting with friends, shopping with friends or alone, etc. In this paper, we extract novel features from Bluetooth traces and use these features for recognizing contextual behavior as well as inferring continuous episode transition. Evaluation results show that extracted novel features are very effective, which enable the model to achieve an average of 87% accuracy for specific context classification and the ability of episode inference from real-life Bluetooth traces.

Author Keywords

Context-aware, Bluetooth, Contextual Behavior, Episode Inference

ACM Classification Keywords

H.5.m Information interfaces and presentation: Miscellaneous.

General Terms

Algorithms, Experimentation, Performance, Human Factors

INTRODUCTION

Context-aware technologies based on mobile devices have been drawing increasing attention of researchers in the ubiquitous computing community due to the increasing use of mobile phone applications. To the best of our knowledge, current research in this area focuses on automatic detection of locations or mobility states of subjects [1, 4], without the ability or potential to infer the subject's current surrounding context. At present, Bluetooth devices are very popular in the world. Amongst the various types of mobile sensors which can be used to serve the purpose of activity, goal or context recognition, Bluetooth sensors have played a primary role in our daily lives but haven't been researched extensively in the current literature. Previous methods based on Bluetooth sensors [2, 3] were not able to classify the context of the subject. In contrast, in this paper we aim to obtain the surrounding context of the subject based on dynamic Bluetooth data **alone**.

Our main contributions are as follows: (1) We extract unique new features based on dynamic Bluetooth information and build a context classification model of dynamic environment. Several representative contexts of our daily lives can be successfully distinguished based on the features (measuring the dynamic changes of inquired Bluetooth devices) we extract from Bluetooth data. (2) We design an episode inference algorithm based on sliding window and context constraint to continuously discover episode transition directly through real-life Bluetooth traces. (3) We investigate our experimental results and compare the performance with recognizing context using accelerometers, WiFi signal strength data and GPS coordinates. As a result, we reveal valuable characteristics of ambient Bluetooth information for both context classification and episode inference.

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PROPOSED APPROACH

In data collection phase, using our mobile phones, we scan surrounding Bluetooth devices every 30 seconds. The Bluetooth devices would respond by sending their information, including their MAC addresses, device names and types.

Bluetooth Context Classification

Given raw Bluetooth data, the first goal is to build a context classification model, which involves Bluetooth feature extraction and classification model training. The following features are selected for a training timeslot: (1)*Quantity of devices*: The number of overall unique devices inquired, which indicates the density of existing devices. (2)*Ratio of static devices*: The ratio of static devices (laptop computers, printers), which is one of the most useful features to distinguish indoor-working state and outdoor state. (3)*Change rate between adjacent samples*: The ration of new devices appeared in a sample compared to the previous sample, which indicates ambient dynamic flow of existing devices. (4)*Duration of devices in view*: In one timeslot, the frequency of occurrence for every device is defined as the duration of one device, which jointly reflects the dynamic changes of surroundings with change rate feature. We aim to recognize six different contexts: *working, walking, taking subway, go shopping, dining, watching movies* as these six contexts are representative contexts in daily lives using C4.5 decision tree.

Episode Inference

To further step, the above model is applied into practical episode inference based on the real-life Bluetooth traces. Besides classifying contexts from a single time slot, we also need to find the episode, which is assumed that lasted longer than 5 minutes and indicated using six contexts that trained by the classification mode. In order to strike a tradeoff between classification precision and boundary accuracy, we propose a sliding window approach. The window size is the training timeslot and the sliding step is one minute. There are two procedures in episode inference, the first is identifying the context of one minute, then inferring the current episode. Each minute will be involved in sliding window several times, thus several classification results would be obtained, and the context of one minute is determined by majority vote rule. While if the context of current minute is different from the last episode, a tolerance interval is used to avoid false determination for episode change. The possible new episode is inferred based on the result of the entire tolerance interval combing with the last episode.

EXPERIMENT RESULTS

In total, we gathered more than 20 hours of available Bluetooth data during three months for six representative contexts, and each context lasts at least 200 minutes. As for the episode inference, we arranged three participants who had different jobs and life styles to collect Bluetooth radio traces for 3-4 weeks as they went about their normal lives.

Experimental results of context classification are determined by 10-fold cross validation. Table 1 shows the precision and the recall values, which could tell the disparity of classification results between different contexts respectively: 1) *working* and *watching movies* have the best classification accuracies, proving the stable context is easier to be distinguished. 2) The recognition rate of *walking* is also acceptable. That is primarily because in this context, the user usually witnesses the most dramatic change in the surrounding information, which can significantly reflected by the features of dynamic Bluetooth information. 3) *T.S* context presents the worst classification effect among all the contexts, a large amount of *T.S* data are misclassified as other contexts. That's because the condition of *T.S* context is very dramatic and the eigenvalue distribution range of *T.S* is very wide, thus it is difficult to find a clear border between the *T.S* and other contexts, especially for two contexts of *dining* and *go shopping*.

	T.S	Wal.	G.S	Din.	W.M	Wor.
Precision	0.82	0.87	0.75	0.80	0.96	1
Recall	0.63	0.96	0.83	0.84	1	0.90

Table 1. Precision and Recall values. T.S means *taking subway*, Wal. means *walking*, G.S means *go shopping*, Din. means *dining*, W.M means *watching movies*, Wor. means *working*, *timeslot* = 5 min.

Another question we are interested in is the influence of quantity of Bluetooth devices on the classification accuracy. Thus we count the recall of every context in terms of the device quantity in one timeslot. The results show that the more ambient Bluetooth devices are inquired, the more credible classification results are achieved. Besides, the effect of devices quantity on the accuracy would become less important gradually as the quantity comes to a fixed amount, which is approximately ten inquired devices in 5 minutes.

Following the initial evaluation on the classification model, we further validate the episode inference algorithm based on the classifier by running it on the real-life Bluetooth traces,

Context	Episode	Acc/WiFi/GPS	Bluetooth
Meeting	Meeting	√	√
	Talking	×	√
Walking	Alone	√	√
	Group	×	√
Dining	Alone	√	√
	Group	×	√
Taking Subway	Alone	√	√
	Group	×	√
Go Shopping	Alone	√	√
	Fri./sep.	×	√
Watching Movies	Alone	√	√
	Group	×	√

Table 2. The comparison for the episode inference. Fri./sep. means the episodes transition, which is that the user is going shopping with friends together, then they depart separately.

where plenty of Bluetooth devices could be inquired in most public places. Seen from Table 2, one large benefit of Bluetooth compared to accelerometer/WiFi/GPS could act as an indicator of episode transition in context. For example, when the user is stationary and having a meeting with many people in the conference room, then after the formal meeting, this user doesn't leave and begins to talk with one or two persons for continuous discussion. Thus, the current context has not changed but the user's episode transforms dynamically over time, which can be inferred via Bluetooth while accelerometer/WiFi/GPS can not. Therefore, Bluetooth based fine-grained surrounding-episode awareness can get more accurate effect to enhance LBS application.

CONCLUSION AND FUTURE WORK

This paper presents a novel approach to recognize the context and episode of the subject using Bluetooth data alone. Firstly, a Bluetooth context classification model distinguishes several typical contexts. This model is further applied into the analysis of real-life Bluetooth traces. The experimental results prove the feasibility of sensing surrounding context and inferring episode transitions through Bluetooth traces adequately. To future study, the one is to make the classification result more accurate particularly when detected Bluetooth devices are sparse. The other is fusion research combining Bluetooth with other sensor technologies.

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