Understanding How Trace Segmentation Impacts Transportation Mode Detection

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ABSTRACT
Transportation mode (TM) detection is one of the activity recognition tasks in ubiquitous computing. A number of previous studies have compared the performance of various classifiers for TM detection. However, the current study is the first work aiming to understand how TM detection performance is impacted by how the recorded location traces are segmented into data segments for training a classifier. In our preliminary experiments we examine three trace segmentation (TS) methods—*Uniform Duration (UniDur), Uniform Number of Location Points (UniNP)*, and *Uniform Distance (UniDis)*—and compare their performance on detecting different transportation modes. The results indicate that while *driving* can be more accurately detected by using *UniDis* method*,* walking and bus can be more accurately detected by using *UniDur* method. This suggests that choosing a right TS method for training a TM classifier is an important step to accurately detect particular transportation modes.

Author Keywords
Trace segmentation; ubicomp; transportation; activity recognition; performance

ACM Classification Keywords
I.5.m. [Pattern Recognition]: Miscellaneous

General Terms
Experimentation; Human Factors; Performance

INTRODUCTION
Mobile location-based applications and services are becoming increasingly popular due to the low cost of sensors such as GPS and the widespread high-speed mobile Internet. Many researchers have sought to develop a variety of location based service for mobile guides, transport support, mobile gaming, assistive technology, and health management [3] that provide services based on users' location, movement dynamics, or trajectory information. The movement dynamics in particular is also used for inferring the transportation mode (TM) of mobile users. Applications such as Ubigreen [1] have demonstrated the use of TM to provide relevant mobile services. However, compared to location, extracting TM information is much more challenging and hence requires more advanced technique such as machine learning to classify different TMs. For example, Conditional Random Fields [6], Hidden Markov Model [2,4], Bayes Network [5,6], Decision Tree [5,6], Support Vector Machine [6], all have been used for achieving such purpose. On the other hand, because mobile users sometimes may change TM during a trip, (e.g., walking to a bus stop to take a bus), researchers have proposed segmenting a trace into smaller trace segments and using them, instead of an entire trace, to train a TM classifier. For example, Zheng et al. [6] has compared the performance of three segmentation modes: by change point, uniform duration, and uniform in TM detection. Their results show that uniform length based method slightly outperforms the other two methods while Conditional Random Field (CRF) is used. However, their results do not distinguish the detection performance among different TMs. In this paper, we argue that *different trip segmentation method may lead to different performances in detecting different TMs*. For example, when uniform length is adopted, because walking is much slower than driving and thus each walking trip segment may contain more location records than a driving trip segment does in same distance, a walking trip segment may be more resistant to noises and outliers than a driving trip segment. To validate our argument, we have conducted two experiments to investigate how TS impacts TM detection performance. Specifically, we examine three TS methods, which are *Uniform Duration (UniDur), Uniform Number of Location Points (UniNP)*, and *Uniform Distance (UniDis).* In order to compare our results with Zheng et al's, we used CRF in our experiments. Our preliminary results show that different TS methods do achieve different performances of TM detection. For example, we found that while *driving* can be more accurately detected by using *UniDis* mode*,* walking can be more accurately detected by using *UniDur* mode.

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EXPERIMENT & RESULTS

The GPS traces we currently own consists of 160 car trips, 55 walk trips, and 36 bus trips. They were collected by 11 people in the past five months. Most traces were collected in Ann Arbor, Michigan, USA. All GPS traces were recorded with Android phones or iPhones. The sampling rates of recordings vary, ranging from one to five seconds, depending on which application the recorders were using. We intentionally did not require all recorders to use the same GPS logger or recording setting because we wanted greater diversity in our data. All traces were applied median filter to reduce GPS noises before they were segmented into data for training.

Experiments

We have conducted two experiments to examine the impact of TS methods on CRF performance in TM detection. Specifically, in both experiments we trained the CRF with data segments generated by the three segmentation methods: *UniDur, UniNP*, and *UniDis*. We evaluated the CRF performance of each segmentation method, each of which with six granularities:

- **Uniform Number of Location Points (UniNP)**: A trace is segmented by every 75, 50, 25, 15, 10, and 5 points.
- **Uniform Distance (UniDis)**: A trace is segmented by every 250, 200, 150, 100, 50, and 25 meters.
- **Uniform Duration (UniDur):** A trace is segmented by every 120, 90, 60, 30, 15, and 10 seconds.

We used CRF++ [7], a widely used CRF toolkit implemented in C++, in both experiments. In Experiment 1, we examine the CRF performance in different window sizes (1 to 5). The objective is to understand whether different segmentation methods would have different levels of impact on different window sizes. In this experiment, we only used fundamental movement features such as average and maximum velocity for training the CRF. The results show that: for detecting bus and walking, the best performances occur in UniDur 120 seconds when window size is larger than 2. However, for detecting driving, UniDis outperforms both UniDur and UniNP for all window sizes. In Experiment 2, we include more features such as maximum acceleration and "stop" information (i.e. how many stops in a segment and how long the stops are) and use only window size 5 to compare the same 18 segmentation granularities. The results show that the top two performances for detecting bus and walking both occur in UniDur 120 seconds (56.3% and 94.9%, respectively), whereas the top two performances for detecting driving both occur in UniDis (99.1% for both 250 and 200 meters). In overall, the best performance in detecting all transportation modes is UniDur 120 seconds (82.9%). The second highest is UniNP 75 points (82.0%), followed by UniDur 90 seconds (79.1%). These results suggest that TS does have impact on TM detection. First, CRF in general performs better when it is trained with larger granularities (e.g. UniNP 75 points, UniDur 120 seconds, and UniDis 250 meters). Second, different TS methods achieve different performances in detecting different TMs.

CONCLUSION & FUTURE WORK

While transportation mode detection has appealed a number of researchers' attention, to our best knowledge we are the first work attempting to formally investigate how trace segmentation impacts the performance of transportation mode detection. As we have shown earlier, a certain segmentation method might be more suitable for detecting a certain transportation mode than the others. This suggests that practitioners and researchers interested in deploying a TM detector on a mobile service would need to consider what transportation mode they are interested in detecting in order to choose a *better* TS method to train the TM classifier. For example, UniDis may be a better option for detecting driving, but it is less suitable for detecting walking and bus than UniNP and UniDur.

To understand the impact of trace segmentation more in depth, our future work includes: a) conducting experiments with more trace features and examine how they are impacted by different segmentation methods, b) evaluate whether the same effect applies to other classifiers such as Hidden Markov Model. The main contribution of this study will be: providing recommendations of good and stable combination of features and segmentation methods that can accurately, reliably, and consistently detect transportation mode.

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