MULTI-STAGE APPROACH TO TRAVEL-MODE SEGMENTATION AND CLASSIFICATION OF GPS TRACES

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ABSTRACT:

This paper presents a multi-stage approach toward the robust classification of travel-modes from GPS traces. Due to the fact that GPS traces are often composed of more than one travel-mode, they are segmented to find sub-traces characterized as an individual travel-mode. This is conducted by finding individual movement segments by identifying stops. In the first stage of classification three main travel-mode classes are identified: pedestrian, bicycle, and motorized vehicles; this is achieved based on the identified segments using speed, acceleration and heading related parameters. Then, segments are linked up to form sub-traces of individual travel-mode. After the first stage is achieved, a breakdown classification of the motorized vehicles class is implemented based on sub-traces of individual travel-mode of cars, buses, trams and trains using Support Vector Machines (SVMs) method. This paper presents a qualitative classification of travel-modes, thus introducing new robust and precise capabilities for the problem at hand.

1. INTRODUCTION

GPS-data nowadays are often collected through mobile handheld devices. As a result, roads, paths and routable traces derived by GPS measurements are collected straightforwardly by pedestrians, public transportation commuters, bicycle riders, car drivers, and more. An updating process of topographic or vehicular data might use the spatial position derived by such measurements to enhance existing quality-inferior and outdated road maps (Schroedl et al., 2004; Zhang et al., 2010); other location-based services could also benefit from such data. Due to the fact that such a geometric enhancement requires the matching of corresponding entities, identifying correctly the road type from which the GPS-trace was collected is important for the implementation of such processes, for example: designated cycleways adjacent to motorways. This research takes six travel-modes into consideration, which supposedly consists of different movement-patterns: walk, bicycle, car, bus, tram and train. The reason is that these modes use different types of road, and separating them from each other will aid matching in the later research of integrating GPS traces with road maps. The assumption is that every GPS-trace stores some unique and relevant characteristics that are derived from a specific travel-mode resultant by the road-type it was acquired on. Most common travel, or traffic, characteristics used in research nowadays (reviewed on the next chapter) are speed and acceleration. Still, these two unique characteristics might not always be sufficient, as ambiguities (different travel-modes might present similar characteristics) and errors are also propagated onto the travel-mode trajectory. This research introduces the use of additional parameters, such as heading and travel time, to achieve more reliable classification results. A problem also arises when a single trace is composed from several sub-traces; each corresponding to a different travel-mode. Thus, the traces should firstly be segmented, and the sub-trace of an individual travel-mode should be separated. The motivation of adopting a multi-stage method is that the three classes: walk, bicycle and motorized vehicles, consist of unique characteristics, which are essential for constructing sub-traces of individual travel-modes. This contributes to the second classification of motorized vehicles only using SVMs method.

2. RELATED WORK

In theory, when compared to classic travel mode survey methods, semi-automatic and automatic classification of travel modes that is based on GPS observations, i.e., trajectories, can contribute significantly be means of accuracy and reliability. Still, since GPS observations alone supply only with geometric and temporal data, specific data-mining methods are applied in order to extract the required information of travel-mode type. Nonetheless, due to the fact that a single GPS-trajectory can be composed of several travel-modes, most approaches include two steps: a segmentation of the trajectory into a series of single travel-mode; and, assigning a specific travel-mode to all segments exist in the series.

A basic assumption is usually made (Chung and Shalaby, 2007) that walking is necessary when a mode-change occurs. This is usually characterized by low values of speed and acceleration, which are used for segmentation; this approach is sometimes referred to as change point-based segmentation method (Zheng et al., 2008). These researches also use the time-length of each segment, assigning some thresholds for the different travel-modes (usually all travel-modes, except for walking and cycling, have the same threshold). Though this approach is usually found to be accurate, the research proposed here suggests using additional characterization of travel-mode values and parameters, such as heading and single travel-mode pattern-classifiers, thus introducing more robust and non-ambiguous segmentation to a given GPS-trajectory.

As for classification, the differentiation between five travel-modes is usually made: walk, cycle, car, urban public transportation (bus and tram), and rail. Most of the existing methods compare some known preliminary travel-mode related measures, e.g. rule-based values, to empirically determined values. Most commonly used values are derived from the speed and acceleration of a segment (single travel-mode), such as maximum and mean speed (Bohte and Maat., 2009; Oliveira et al., 2005; Stopher et al., 2005). Another method suggests using particle filters using Expectation-Maximization that is based on learning of a Bayesian model (Patterson et al., 2003). Still, it was shown that these approaches might present ambiguous-classification, thus yield errors and lack the flexibility to examine properly change in pattern and uncertainty of the travel-mode. Also, the determination of these thresholds is also sometimes biased from specific travel-logs (GPS-trajectories) used for analysis, i.e., the thresholds depend on a specific study-area and supplementary data. Thus, these methods are not always generic to be implemented for all environments and test-data. To overcome the uncertainty and ambiguity exist in the data, the use of fuzzy logics as a replacement for the empirically determined values is also suggested for classification. The speed and acceleration measures are related as fuzzy sets, while fuzzy membership patterns are structured to enable travel-mode classifiers via linguistic rules (Tsui and Shalaby, 2006; Schuessler, 2008). Although these researches show an improvement in robustness of classification, the determination of bounds for each linguistic rules associated with each measure was found to be depended on subjective experience exist in the travel-logs. Fuzzy pattern recognition together with existing fuzzy logic classification (Xu et al., 2010) showed some advantages over previous work, but still, some levels of uncertainty were remain evident. A Decision Tree is also used (Reddy et al., 2008; Zheng et al., 2008). In the first research the authors present its superiority to other approaches commonly used; where in the latter research, the authors show that together with a first-order Hidden Markov Mode they have received promising results for classification. Still, in this case all motorized vehicles were considered as one single travel-mode - as opposed to the commonly used three travel-modes - and also their training data was relatively small. It is also should be emphasized that the latter research used also supplementary accelerometer data for classification. This type of information is being widely used in recent researches; sometimes together with preliminary knowledge about the transportation network exist in the study-area (Troped et al., 2008; Gong et al., 2011).

Overcoming the problems and ambiguities aforementioned, this research proposes a multi-stage classification, which introduces specific classifiers on every stage to overcome data uncertainties exist otherwise - introducing a process that is more robust. Also, it should be emphasized that six travel-modes are introduced here – and not merely five – where the urban public transportation travel mode is divided to two classes: bus and tram; thus, expanding the potential of the classification process and introducing new capacities.

3. DATA COLLECTION

3.1 Study Area

This research is focused on the urban region of Hanover City. GPS traces are collected using handheld mobile devices equipped with GPS via a designated application was developed specifically for this research. In order to evaluate the experiment results the specific travel-mode was also recorded by the mobile devices – and not only the location. The data collection period simulates the natural way of how people travel in their everyday life without applying any special concerns or restrictions.

3.2 Tracer Android App

For the statistical appreciation of the proposed travel-mode classification methodology, a training data with supplementary information is required. For this, an Android application was programmed in Java, which collects GPS data and reference added-data (tagging) that basically store the travel-mode specified by the user. The application (in the mobile domain usually referred to as App), named *Tracer*, was specifically designed to be used for Android-based Smartphones. The Graphical User Interface, depicted in Figure 1, presents specific and easy-to-use functions. These functions include: a toggle button for starting and stopping data acquisition (left); and, a button enabling the user to select (and modify) his current travel-mode (right). The user can choose from six different travel-modes that are used in this research: Walk, Bike, Car, Bus, Train, and Tram. Additionally, there exist a checkbox labeled "silent" (left), which allow the user to choose whether to be notified with some predefined events – detailed later.

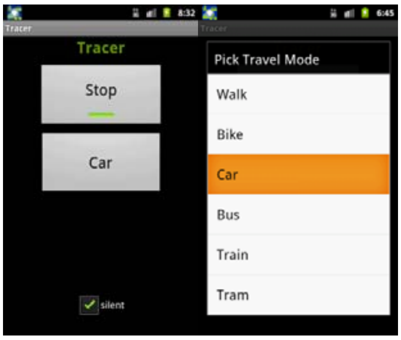

Figure 1. Graphical User Interface of the *Tracer* App: main view (left); and, travel-mode selection (right)

Since the data acquisition is supposed to be a passive procedure, the *Tracer* App provides with a notification system that requires the user attention on specific predefined events. The notification system utilizes all modes of user notifications provided by modern smartphones, e.g. visual, sound and haptical. Their common goal is to obtain the user's correct current travel-mode. The Tracer App implements the following events:

- The constant travel-mode update event forces the user to update current travel-mode every 10 minutes in order to prevent from forgetting to do so.
- The GPS-signal loss event is triggered only after gaining back of signal, which was lost for more than 20 seconds. This includes cases where travel-mode changes might happen without having a GPS-signal.
- Speed inconsistency cover events of derived travelling speed exceeding predefined speed limits for walking and cycling that are over 10 seconds. Thresholds used are coarse, and as such are only a type of warning.

4. SEGMENTATION AND CLASSIFICATION METHODOLOGY

As mentioned before, a GPS trace is not necessarily derived from a single travel-mode; instead, it is often composed of several different travel-modes, depicted in Figure 3 (top). Before any classification is carried out, a separation of the trace into segments of an individual travel-mode has to be implemented, which are characterized as sub-traces. A sub-trace is composed of a single travel-movement segment separated by two stops. After all segments composing a single GPS-trace are identified, the classification is applied on these segments,