A new algorithm for mode detection in travel surveys

(Cost Action SHANTI)

Background
Travel surveys are an appropriate means for collecting disaggregate data on people’s travel behaviour, in particular the number of trips, origin and destination, duration, length, mode, and purpose of travel. Traditional paper-pencil or telephone interviews are widely used and well established in person-based travel surveys. The main issues with these methods are enormous burden on respondents and an unknown extent of missing, wrong or inaccurate data. Current research revealed that trips are underreported by as much as 25 % on average in conventional trip diaries (Kohla and Meschik, 2012).

In the last years sensor technologies were established more and more in order to improve data quality and reliability of mobility data gained from travel surveys. Portable GPS-devices with built-in accelerometer or smartphones with additional sensors provide a continuous data stream on the position, movement and environment of a person. These primary sensor data need to be processed and interpreted in order to derive the actual mobility figures, which a travel survey is expected to deliver. The first generation of GPS-supported surveys used prompted recall interviews for this task. They are very time-consuming and expensive and can thus be just a bridging technology. An efficient handling of prospective, technology-based travel surveys relies on automatic processing and interpretation of sensor data. It requires reliable algorithms and procedures, which are not available so far. Current research focusses primarily on the automatic detection of trip stages and travel modes, but further problems must be solved as well, e.g., the automatic identification of trip purposes and activities in order to reveal individual trips in the continuous data stream.

The first attempts at an automatic identification of travel modes, which solely used GPS data, did not perform sufficiently. But, the increasing availability of accelerometers on mobile devices offers an opportunity for improvement. Some few studies are already available, which were dealing with both GPS and acceleration data, but corresponding research is only at its beginning. There is still need to explore different approaches, to compare these approaches in a systematic manner, and to come up with a procedure ready for use in practice.

Objectives
The current study is about a new procedure for the automatic identification of trip stages and travel modes, which is based on the data obtained from accelerometer equipped GPS devices in travel surveys. The procedure is at first described and afterwards compared to alternative approaches in terms of performance and usability.

Data basis
The reference data derive from a pilot study (MobiFIT consortium 2011), which combined different survey methods to analyse applicability and limitations of GPS technology in travel surveys. The respondents were asked to carry passive accelerometer equipped GPS devices for three days and were interviewed afterwards (prompted recall) to complete details of trip stages (e.g. travel mode). 134 respondents reported a total 2,036 valid trip stages (346 hours of travel), which were used for the development of the procedure for automatic
Mode detection. The acceleration data were recorded 10 times per second in three axes, the GPS data every second (time, position plus additional data). 229 features were derived from both sources, which served as possible predictors of the travel mode. Another 25 features on socio-demographic characteristics and available travel options of users were deduced from the interviews.

Mode detection procedure
The automatic detection of travel models can be referred to as classification task in the realm of machine learning. This task consists of three steps, each of which can be performed by several different methods. The methods mentioned in the following are just examples, there are even more options available at each stage:

- feature generation by means of frequency analysis or analysis of distribution characteristics;
- feature selection by means of covariance analysis, stepwise regression, or random subspace selection;
- classification by means of discriminant analysis, naive Bayes classifier, logistic regression, support vector machine, or decision trees.

The selection of the method at a given stage is more or less independent from the methods used at other stages, and each method involves several sub-options, resulting in an endless number of possible procedures. Our study is not only new in terms of a 'new combination' of methods. To the best of our knowledge, some of the methods used by us have never been used before for automatic mode detection. They are described in the following along with the reason why we have used these particular methods.

-> Feature generation: A particular focus is on the features derived from the 3D-accelerometer, since they are more complete and accurate than GPS data due to the independence from satellite reception. Moreover, they are hoped to provide the most reliable indicators of travel modes. Previous studies have employed frequency analysis for this task, but we derived multiple distribution characteristics from the amplitudes and periods of the primary sensor signal. We followed the assumption that periodic frequencies detected by the accelerometer are no reliable indicators of travel modes because of huge individual variability caused by differences in step length, speed, road surface, shock absorbers etc. Nonetheless, there are systematic differences in the aperiodic vibration pattern, which may provide robust and reliable indicators of different travel modes. Beyond the 3D-accelerometer, we used several additional data sources in terms of GPS data, movement characteristics, user characteristics, and availability of travel modes (e.g. car ownership).

-> Feature selection: This step has a theoretical and a statistical aspect. In theoretical terms, we performed a hypothesis-based selection: We assume that different data sources differ in the degree of being influenced by other factors than the chosen travel mode. As an example: a close match of individual stops with the location of bus stops may indicate that the person was travelling by bus – but this pattern could also be generated by a person travelling by car, if the bus stops are located at traffic lights, what is common practice. As a result, the data sources also differ in their reliability for mode detection. The highest reliability is assumed to be with acceleration features, followed by GPS, movement, and personal features. An acceleration feature would thus be preferred over a personal feature in case of equal statistical performance. In statistical terms, stepwise regression was employed for feature selection.

-> Classification: Among the numerous options available, we used multinomial logistic regression, because it is well introduced and widely used in transportation research, e.g., for discrete choice experiments. Two regression models (one pedestrian-optimised and one optimised on all modes of travel) were trained by
empirical travel data gained from prompted recall interviews. Different classification rules were tested based on the given probabilities of occurrence.

These methods were embedded in an overall procedure including pre-processing, as described by Kohla (2012). We assume that each mode change induces at least a short pedestrian stage in-between, because people must walk to the next mode. This argues for a two-step procedure:

(i) Detection of pedestrian stages and mode changing points by means of a pedestrian-optimised model. Data in-between two pedestrian stages are supposed to refer to the same travel mode.
(ii) Generation of features (acceleration pattern, movement etc.) for the 'non-pedestrian stages' and detection of the remaining modes (except pedestrian) by a second classification model.

Results
The models of both steps were trained separately using empirical data. In the first-step model, 95 % of pedestrian stages were identified correctly with the acceleration data alone. The inclusion of GPS data increased the detection rate to 96 %. In the second-step model (8 mode detection), 78 % of trip stages were classified correctly with the acceleration data, and 85 % after integrating GPS data. Those features derived from user characteristics and availability of travel modes failed further improvement of both models. We found that pedestrian, car and railway obtained better results, whereas bicycle, bus and tram caused some difficulties in detection. An integration of additional data sources (e.g. data on infrastructure, quality of service, additional sensor data of smart-phones), an extension of features as well as improved data quality and quantity promise further improvement, especially concerning the detection of bicycle and public transport.

An application of the two-step mode detection procedure to a dataset with unknown mode changing points revealed correct detection of travel modes during 79 % of the observation time. Further improvement of algorithms is in progress and overall detection rates higher than 80 % can be expected.

These results can be interpreted in two different ways: (i) Is the performance sufficient for practical use? This question can only be answered in the long run, because it relies on practical experience. We feel that a satisfying detection rate overall examined travel modes should be somewhere above 95 % (ii) How is the performance in comparison to alternative approaches, which serve the same purpose? In order to answer this question, we collected some key figures from other studies reported in the literature:

- Deterministic rules by Bohte and Maat (2008) or Clifford et al. (2008) (GPS only)
- Bayesian Belief Network by Feng et al. (2011) (GPS and acceleration)
- Fuzzy Logic by Rieser-Schüssler et al. (2011) (GPS and acceleration)
- Decision tree and first-order discrete Hidden Markov Model by Reddy et al. (2010) (GPS and acceleration)
- Random subspace model by Nitsche et al. (2011) (GPS and acceleration)

The final paper will provide a comparison of the current study with those reported in the articles listed above. It will not be a meta-analysis, because there are too few studies available, which differ in too many respects. But, the comparison will take several criteria into account, which refer to data sources (e.g., with or without 3D-acceleration), feature generation and feature selection methods, classification algorithms, number of modes, goodness of fit measures, and mode detection rates.
References


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