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Travel mode estimation for multi-modal journey planner

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ABSTRACT

For route planning and tracking, it is sometimes necessary to know if the user is walking or using some other mode of transport. In most cases, the GPS data can be acquired from the user device. It is possible to estimate user's transportation mode based on a GPS trace at a sampling rate of once per minute. There has been little prior work on the selection of a set of features from a large number of proposed features, especially for sparse GPS data. This article considers characteristics of distribution, auto- and cross-correlations, and spectral features of speed and acceleration as possible features, and presents an approach to selecting the most significant, non-correlating features from among those. Both speed and acceleration are inferred from changes in location and time between data points. Using GPS traces of buses in the city of Tampere, and of walking, biking and driving from the OpenStreetMap and Microsoft GeoLife projects, spectral bins were found to be among the most significant non-correlating features for differentiating between walking, bicycle, bus and driving, and were used to train classifiers with a fair accuracy. Auto- and cross-correlations, kurtoses and skewnesses were found to be of no use in the classification task. Useful features were found to have a fairly large (>0.4) correlation with each other.

1. Introduction

Knowing the mode of transportation currently employed by the user has many applications. Among these are tracking the user's exercise goals (Parkka et al., 2006), more accurate household travel surveys (Gong et al., 2012) and better informed participant selection for such surveys (Reddy et al., 2009), as a precursor to trip purpose recognition (Xiao et al., 2016), and even targeted advertisements (Zhu et al., 2016).

Studies have been carried out on learning users' daily activity patterns for demand forecasting (Allahviranloo and Recker, 2013), and for building agent-based simulations (Liao et al., 2013). Knowing the users' mode of transport to the latest activity would assist in prediction of scheduling.

The effect of travel time variability on flexible scheduling has also been studied (Jenelius, 2012; Fosgerau and Karlström, 2010). Since the variability of travel time is dependent on the mode of travel, knowledge of the user's previous travel mode could be used to further optimize the scheduling.

The motivation for the system described in this paper is the intent to incentivize ecological transportation choices in the city of Tampere. For this purpose, a method to identify walking, biking, driving and taking a bus is needed. The intent is to use data gathered by logging the user's location at intervals of one minute, which means that any features must be inferred from the coordinates and timestamps of datapoints.

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In this paper, skewness, kurtosis, auto- and cross correlations, and energy spectra of speed and acceleration are considered as potential features for travel mode identification.

Three criteria are used for the selection of the most significant features for a machine learning algorithm. To validate these three methods, three different machine learning algorithms are trained based on the results of the three selection criteria, and compared.

The selected features are used to train a four-class feed-forward neural network, a four-class Bayes classifier, and a decision tree based on consecutive Bayes classifiers. The principle behind these classifiers is explained in Section 3.

The training data consisted of GPS traces of Tampere city buses and GPS traces acquired from the OpenStreetMap and GeoLife project. The preprocessing for this data is described in Section 4.

The selection criteria used are Welch's *t*-test, Mann-Whitney *U*-test, and *F*-test. The process of selecting features is outlined in Section 5. For comparison, a stacked autoencoder was also used in conjunction with a single-layer neural network.

A neural network was found to have the best F1-score with each selection criterion. Adding a second or third layer to a neural network yielded marginal improvements for two out of three criteria and marginally worse results in a third. Using an autoencoder rather than the manual dimension reduction produced the worst results. More in depth results are outlined in Section 6, and discussion of the results is given in Section 7.

2. Background

2.1. Related work

Travel mode recognition has been studied a lot. Most studies have used an accelerometer alone or combined with a GPS unit. A common theme in the research is that walking can be identified with over 90% accuracy.

Su et al. (2014) made a fairly broad literature review on the subject of recognizing the user's activity using smartphone sensors. They listed a large variety of features that have been used, classified to time domain and frequency domain features applied to an accelerometer's output.

A more recent literature review, Prelipcean et al. (2017), identified three research areas that use travel mode recognition: Location based services, transportation science and human geography. Each of these has slightly different demands. Location based services require close to real-time information about the user's location and current mode of transport. Transportation science concerns itself with statistics of users' modes of transport, and requires accuracy more than speed. Human geography seeks to enrich traces with domain-specific information, and its travel mode detection is focused on segmenting traces into stops and moves.

Using only timestamped coordinates to extract the features was rare. In particular, using the GPS speed data was common (Reddy et al., 2008; Sun and Ban, 2013; Bolbol et al., 2012). Using an accelerometer in conjunction with a GPS receiver has also been studied (Reddy et al., 2008).

Table 1 on page 6 shows an overview of classifiers and features considered in various studies, as well as the accuracies achieved. If more than one classifier was considered, the best-performing one is in bold.

Features that have been considered have varied. Means and variances of acceleration and speed are common. Rarer examples are other features of the distributions, and spectral features. Some studies (Gong et al., 2012; Stenneth et al., 2011) used Geographical Information Systems (GIS) to estimate a trace's similarity to a public transport route. The amount of heading change has also been considered, although it has generally been found lacking.

Selecting the best features to use presents a problem in any classification task, and particularly in travel mode recognition where the literature provides a wealth of features to select from. Bolbol et al. (2012) used Wilks' Lambda test and between-groups *F*-test to select the most significant features. They also noted that, by 2012, travel mode recognition studies rarely considered feature selection. Stenneth et al. (2011) ranked the features by Chi Square and Information gain algorithms.

Sun and Ban (2013) raised privacy concerns regarding the frequency of sampling the GPS data, and suggested that research should be done on how sparse data can be used. Bobol and Cheng (2010) demonstrated that 30–60 seconds' sample time is sufficient for this purpose.

2.2. Hypotheses

Hypothesis 1. Frequency-domain features can be used to differentiate between modes of transportation.

A number of factors could be expected to create fluctuation in the speed at which a person or vehicle is traveling at. For buses, there are stops along the way which would necessitate coming to a full stop to load and unload passengers. All traffic would be expected to pause or slow down at intersections, but cars and bicycles would reach the intersections faster than walkers.

Frequency domain features have been used in travel mode recognition via accelerometer (Kwapisz et al., 2011), and on dense GPS data (Reddy et al., 2008). However, little research was found studying the spectral features of sparse GPS data.