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Optimizing mobile device GPS data collection to capture long distance travel

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Abstract

There is significant interest in using smart phone devices for a range of travel behavior data collection applications. However, the frequency in the rate of GPS data collection creates conflict between the quality of data obtained and longevity of device battery life. This paper reports on a project that trialed the use of a passive activity logger named *Moves*. The goal of this project was to examine the ability of a passive activity logger – in the form of a smart phone application - to collect GPS data points for long distance travel origins and destinations. The app was designed to optimize long distance (>50mile trips) travel behavior data collection, with goals of minimizing frequency of collection and maximizing trip reporting accuracy. The results showed optimal accuracies of up to 92% with drastically reduced volume of data points collected by the passive activity logger. These findings will be of significant interest to others seeking to use smart phones in travel behavior research, and also open pathways for researchers in related fields such as tourism to undertake time and place-specific research.

1. Introduction

Travel survey data collection has moved from pen and paper surveys through random-digit telephone interviews to using the internet and smart IT devices. This has opened up new opportunities for researchers and provided improvements in the quantity and accuracy of travel data that can be obtained. In particular, global positioning systems (GPS) data streams collected passively from participant's devices can be used to measure an individual's movements more accurately and with fewer missed trips (Bachu, Dudala et al. 2001). The reduction in respondent burden due to passive data collection allows for more participants to be involved in a study, offering improved results (Bekhor, Cohen et al. 2013). Long distance travel (LDT) has been underrepresented in travel surveying due to constraints on the amount of time that a survey can take place and the number of participants that may take part in a study (Stopher, Kockelman et al. 2008). LDT, as defined by this study, is any trip from an origin to a destination that is greater than 50 miles (80km). Surveying people after their return from such long-distance trips creates problems as participants

have recall biases that may cause them to forget trip information and inaccurately estimate the distances that they traveled (Wolf, Guensler et al. 2001 , Wolf 2004). LDT researchers are seeking approaches and methods that can increase our ability to study this previously evasive form of movement. If researchers can develop such methods they could be of use across fields as diverse as travel behaviour, transport geography, tourism, road safety and freight.

The goal of this project was to examine the ability of a passive activity logger – in the form of a smart phone application – to collect GPS data points for long distance travel origins and destinations. The approach used was comparative, using a smart phone app to passively collect data from participants and comparing the outputs with self-reported travel data. A particular focus was in accurately identifying long distance trip origins and destinations. We obtained a 24-hour GPS dataset to allow us to optimize the rate of data sampling sampled, and the time periods that data is collected, so as to collect the best possible dataset from such a device. If successful, this approach would help clarify how often and at what times a smart phone should collect GPS data points to measure LDT, and also open pathways for a range of other behavioral surveys both within and beyond the field of transport research.

In routine travel surveys conducted on mobile devices, higher levels of battery use associated with large amounts of data collection creates serious issues. Battery drain can cause participants' phones to 'die', reducing accuracy of the data collected and affecting participant retention (Jariyasunant, Sengupta et al. 2012). A detailed understanding of turn-by-turn movements is not usually needed in long-distance studies, and is somewhat unnecessary if focusing on air travel. However, there is little research to date on the required frequency of data collection for LDT behavior, and what is sufficient to capture overall LDT origins, destinations, and trip rates. More data points do not necessarily mean greater accuracy, as participants may remain stationary for large parts of the day, such as when sleeping or working. However, if data is captured too infrequently, day trips of short duration may be missed. Our approach was to experiment with the settings for data collection on a smart phone app, adjusting the number of data points selected each day, to identify LDT origins and destinations. To identify optimal methods, we compared data selected from our GPS streams to self-reported data from participant interviews, allowing us to determine how well each methodology was able to capture long distance trips, reduce incorrect trip collection, report LDT mileage, and return accurate GPS locations for origin and destination points.

Our focus is methodological. This paper first describes the previous developments in the field of long distance travel surveying and the use of mobile phones and GPS in data collection. Next it outlines the data collection methodology implemented in this study, as well as the data cleaning and GPS location pairing algorithms. The accuracy and effectiveness of each algorithm is presented with its ability to represent long distance origins and destinations. Finally, we discuss the limitations of the approach, the implications for travel behavior research, and look at possible future research directions.

2. Literature Review

GPS data collection devices have become a common method of travel behavior data collection since their introduction to travel surveying in the late 1990s (Wagner 1997). We will turn now to look, in turn, at these types of surveys, the devices themselves, and the issues involved with their use.

2.1. GPS Travel Surveys

Shen and Stopher (2014) produced an up-to-date review of GPS-based travel surveying and processing, identifying studies using smart-phone devices in 14 different countries (Shen and Stopher 2014). GPS data logs, often from in-vehicle GPS devices or in smart phone apps, have most commonly been coupled with travel survey diaries to verify the accuracy of the data collected in household travel surveys (Bricka and Bhat 2006 , Bohte and Maat 2009). Connecting GPS data to localized maps allows extrapolated trip ends to aid in reporting trip purposes based on information about origins and destinations (Wolf, Guensler et al. 2001 , Bohte and Maat 2009 , Montini, Prost et al. 2015). These inferences decrease user burden by reducing the amount of data they must record for each trip, once again allowing for larger sample sizes and better understanding of long distance traveler behavior.

2.2. Collection Devices

Collection devices have become more advanced and many varieties of devices are now available to the researcher. Originally, collection was done solely in-vehicle (Wolf, Schonfelder et al. 2003 , Wolf 2004). In-vehicle GPS collection devices are capable of accurately collecting turn-by-turn travel in automobiles. But they have drawbacks, such as the lack of ability to track non-vehicular travel. Battery issues with in-vehicle GPS devices are limited as they draw their power from the vehicle itself. Collection of data is easily limited to when the automobile is powered on, thus reducing the amount of extraneous data collected during the study (Stopher, FitzGerald et al. 2007). Issues arise when automating the detection of short duration trips, as well as preventing traffic lights and congested roadways from appearing as trip ends. Dwell time, the use of stationary behavior for a period of time as an indicator of trip ends, was introduced as a way to improve passive data collection, and parameters have been created to optimize the number of missed trips without obtaining false trip stops (Stopher, Bullock et al. 2002 , Wolf, Schonfelder et al. 2003). Dwell time thresholds with confidence ratings have been devised to detect trips based on length of time of non-movement. The longer the lack of movement, the more likely the stop location is a trip end. GPS also functions by contacting satellites to obtain a location through triangulation, locating the device on an X, Y, Z coordinate plane. As in-vehicle GPS systems use the car battery to obtain power, sometimes origins of trips are misreported due to the time it takes to acquire a "fix" on satellites (Montini, Prost et al. 2015) and correctly obtain origin location. On-person GPS devices, including smart phone apps, have increasingly been used to track non-vehicle travel such as walking and biking trips (Stopher, FitzGerald et al. 2007). Results demonstrate that early, heavy GPS devices were prone to being left at home on many trips, resulting in underreporting and errors in data (Wolf 2004 , Draijer, Kalfs et al. 2010). As devices became smaller, user burden issues moved from the carrying of the device to issues with charging the GPS device itself (Bohte and Maat 2009). At first, the ownership of devices and delivery to users decreased the ability of researchers to have large sample sizes (Cottrill, Pereira et al. 2013). But most of these issues have been overcome by the ubiquity of smart phones in contemporary Western societies [albeit with some key population group exceptions] and the increasing capacity for skilled researchers to design smart phone apps that can be readily delivered onto one's existing device.

2.3. Cell Phone Usage

Smart phones are in frequent communication with infrastructure, and have the ability to accurately and efficiently collect GPS data while already occupying space in both people's pockets and their charging schedules. Many cellular positioning studies have now been completed to analyze the potential effectiveness of cellular devices and their many sensors for transportation surveying. Throughout the literature, two main cell phone sensors have been used to determine specific location of participants:

- the phone's cellular position from triangulated towers (Liu, Danczyk et al. 2008 , Bekhor, Cohen et al. 2013 , Xu, Shaw et al. 2015); and,
- the phone's internal GPS system (Wolf, Guensler et al. 2001 , Stopher, Bullock et al. 2002 , Wolf, Schonfelder et al. 2003 , Bricka and Bhat 2006 , Du and Aultman-Hall 2007 , Bohte and Maat 2009 , Jariyasunant, Sengupta et al. 2012).

Other sensors such as Bluetooth have been used to determine highly specific movement characteristics, not necessarily location, and are not of interest to this study. For more on the use of auxiliary sensory data methods to determine travel mode types see Shafique and Hato (2016), Zhou, Yu et al. (2016), and Eftekhari and Ghatee (2016).

There is a specific issue regarding GPS data collection on personal cellular phones as it greatly increases the amount of battery power that devices consume. This becomes particularly relevant when one considers LDT. Battery life issues are of major concern as smartphones have responsibilities besides their use as travel diaries (Stopher, FitzGerald et al. 2007 , Jariyasunant, Sengupta et al. 2012 , Montini, Prost et al. 2015). More efficient activation of a GPS sensor is needed to improve battery lifespan (Zhuang, Kim et al. 2010). Further, many users must switch off their phones when using particular modes of transport, such as commercial aircraft.

2.4. Passive Data Collection

Travel data collection processes can be separated into two categories: user-flagged and passive. User-flagged systems require the participant to initiate and terminate data collection during their trips, thereby determining trip starts and stops. This increases user burden and introduces human inaccuracy as participants may forget to initiate or end trips, even with prompting. Passive data collection requires no interaction with the participants, limiting user error and burden by automatically inferring trip ends based on movement characteristics (Stopher, FitzGerald et al. 2007 , Bohte and Maat 2009). Research into passive data collection has led to further development into intelligent collection methods. By determining a certain time frequency for collection, over- (or under-)collection of data can be avoided. Additionally, speed-based collection allows for data to only be collected while the participant is in motion, reducing erroneous data collection, battery usage, and frequency of connection to a server while participants are stopped for long periods of time (Srinivasan, Bricka et al. 2009).

2.5. Issues with Long Distance Travel Surveying

Shorter, urban trips make up the greatest proportion of people's travel, yet LDT occupies a large amount of the total mileage travelled and contributes significantly to Greenhouse gas emissions (Kuhnimhof, Collet et al. 2009). But the proportions of local vs. long distance travel are changing. US urban and rural miles travelled by car have been decreasing in recent years (Puentes and Tomer 2008), while air traffic has surged, producing greater passenger miles travelled (Organization 2018). LDT is hard to measure because it is uncommon at an individual level and participation is uneven across the population (Limtanakool, Dijst et al. 2006) as it is highly reliant on economic prosperity. With economic growth, people are able to afford to travel at faster speeds allowing them to reach more distant destinations within their allotted time budget (Schafer 1997). They are also likely to undertake more long distance travel, based on economic capacity.

Surveys such as the USA's National Household Travel Survey (NHTS) ask respondents to recall their trip-making for a specific period of time, often between one and four days. This works adequately for frequent trips such as urban travel where a forgotten trip does not drastically shift the results due to large trip volumes. Long distance travel occurs much less frequently. It therefore requires much larger sample sizes in order to accurately collect data for short study periods such as those used in the NHTS.

Previous methods of long distance travel data collection have generally been bespoke, to suit the particular research need of the study concerned. Virtually every LDT survey we reviewed had its own definition of long distance travel, making comparison of results difficult. For example, LDT has been defined as being trips greater than 80km as the crow flies (Zhuang, Kim et al. 2010), trips >100km via the road network by key French agencies (Zumkeller, Chlond et al. 2006), a trip with an overnight stay and an excursion of greater than 3 hours (Kunert, Kloas et al. 2003), and trips of >50 miles in the UK National Travel Survey (Commission 2010). There are similar inconsistencies between what is defined as a trip-stage on these journeys, and the level of detail captured on these trips.

3. Methods and Data

This study implemented a passive GPS data collection on participants' mobile devices to collect 24-hour GPS location data. These 24-hour logs were used to create LDT logs by extracting participant location at certain times of day, and then examining that GPS data for movements greater than the designated long distance threshold. A distance of 50 miles as the crow flies was selected by the research team.

3.1. Methods Overview

This study implemented periods of check-in between 1-24hours. This was deemed as an appropriate length of time as the data collected represents large-scale movements across space, as opposed to the small-scale turn-by-turn behavior found in traditional GPS surveys. This examination creates an LDT log; with each origin and destination GPS point, and the local time and date it was collected. At the end of the study period, participants were also interviewed to obtain self-reported long distance trip information for the same period. The use of the activity logger, *Moves*, which provides visuals of participant movements overlaid on Google Mapping software. Each trip's origin, destination, and date that the trip was taken were recorded in a text format. These data were then converted into GPS coordinates to allow comparison to the data collected by the mobile application. The long distance GPS data was then compared with the interview data. Each long distance trip extracted has an origin and destination, which are compared with the interview responses. Buffers were used to allow for trips originating or ending within the 24 hour survey period, but which had a starting or end point outside that 24 hour window. Experimentation was then employed to test many different combinations of data sampling times and the rate of reporting per day. The study was able to isolate the minimum number and times of day a phone should passively collect GPS data to accurately collect LDT origins and destination, reduce battery drain, and reduce participant burden. There are limitless possibilities when choosing times of day to analyze for potential accuracy in data collection. For this study, we decided to limit our data extraction to the beginning of each of the 24 hours of the day. Thus the maximum number of unique data points that could be returned each day was 24. A minimum of one data point was tested to determine accuracy of the algorithm.

3.2. Data Overview

To process GPS data, *Python 3* software was used, alongside the programming library *GeoPy*. The most relevant steps when generating long distance travel trip logs are:

- Processing of data into 24-hour logs.
- Selection of data based on input variables.
- Comparison of long distance trips to true data collected using NGSA-II.

3.3. Study Participants and Interviews

Twelve participants were recruited for this study from the University of Vermont Transportation Research Center, and through personal networks of the researchers. Participants were mostly young, white, middle-class, male (there were five women), owned and used smart phones, and were either in college or college-educated. The mobile phone application *MOVES* was installed on twelve IOS devices for 2-13 months to collect GPS data. At the end of this period, participants were contacted to conduct an exit interview and export their data. These interviews allowed for the collection of LDT logs that each participant completed during their time in the study. Of the 12 participants, 10 fully completed the exit interview and final data collection. Of the two other participants, one was unable to meet during the available interview times and one had technical difficulties exporting their data.

At the culmination of the data collection period, participants were contacted to complete closing interviews. At this time, participants were given detailed instructions on the process of exporting their GPS data for researchers to analyze. Participants were also told to bring any tools that might aid in their recollection of any Long Distance trips they took: personal calendars, any itineraries they had compiled, their email accounts, and the *Moves* application itself. They were informed that for the purpose of this study, a long distance trip was defined as any movement from an origin to a destination that was greater than 50 miles. If a participant was unsure if a trip they took fell into that threshold, they were asked to report it and it would be checked by the researcher for accuracy at the culmination of the interview. During the interview, participants were asked to state the date that each trip took place, the origin location, and the destination location. Location City and State names were recorded for trips inside the US. For trips outside the US, the Country's name and City name were recorded.

After the interviews were completed, the Moves GPS data was used to check that participants did not forget any trips. Researchers extracted movements of greater than 50 miles from the GPS data and any trips that were found, but went unmentioned, were presented to the participant to see if they had taken the trip, or if it was an incorrect GPS recording. If the participant confirmed the presence of a missed trip, that trip's information was added to their interview data. Through this process, the researchers are confident that each long distance trip participants took during the study was correctly recorded.

3.4. Collection Application

The *Moves* app acts as an activity log and passively collects GPS data based on device movements. *Moves'* ease of installation on participants' devices, the ease of export of GPS data, and the application's ability to collect data indefinitely without any participant interaction were all factors that made it a viable choice. For this study, GPS data was exported from *Moves* in JSON format and was analyzed using the coding language, Python. After export, it was converted into a travel log, with GPS coordinates and time stamps tracking each participant's movements throughout their time in the study. GPS points were tagged as either a Place or a Movement dependent on the user's behavior. These points make up a 24-hour log of each user's location throughout their time in the study.

3.5. Matching Interview and GPS Data

A goal of this research project was to directly compare machine recorded GPS data with interview trips for the same travel. The post processing of data in order to match these two trips was much more difficult than expected due to a number of reasons.

- Trips collected in participant interviews lack start times, length of time travelled, or distance between origin and destination.

- Interview trips lack exact origin or destination GPS locations; rather they only include city names, leading to lack of specificity.

- Trip start and end dates may vary between interview data and GPS data depending on what time of day the trip was taken and when the GPS point was selected from the travel log.

Travel distance measurements vary between GPS and Interview data. The GPS location recorded by the mobile device will measure the exact location selected for that trip. The Python library, GeoPy was used to match City and State/Country names returned by participants in interviews with city center GPS locations. With the interview data and the Moves data in GPS format, it became possible to test each method of GPS data extraction for accuracy.

The Moves location may be collected while at the final destination, or en route to that location. In the interview data, the final destination is simply the GPS city centroid of the named location provided during the exit interview. City centroids were used as many interviewees were unable to provide exact addresses for their travel locations, caused by lack of local geographic knowledge. Interviewees were often only able to name the cities they traveled to. This is a limitation as not all travel was made near these centroids. Therefore during our matching process, if the returned GPS origin or destination is within 50 miles of the interview data, it is marked as a correctly identified trip. During the study period, the participant's phone may have been turned off at the start, during, or at the culmination of each trip. Thus one needed to both look for matches of GPS trips with corresponding interview trips, but also look backwards for missing GPS trips in the interview dataset.

3.6. Result Optimization

In order to determine the best times of day to collect data, and compare these points, this study implemented a multi-objective evolutionary algorithm (MOEA). The specific MOEA was a non-dominated generic sorting algorithm, NSGA-II, in the Python programming language.

This test had two objectives (Number of Times, What Time), with 24 possible dimensions (each hour of the day). Each possible solution, a candidate, is then compared to all other generated candidates based on its performance with regards to the objectives. Each candidate has two characteristics calculated for it: the number of times it performed worse than other candidates (domination), and the set of candidates that it dominates. Each candidate with domination counts of 0 are maintained as the top candidates, while the rest are removed from the remainder of the analyses.

Number of Possible Data Combinations
$$\sum_{k=1}^{n} \frac{n!}{k!(n-k)!}, for\ 0 \leq k \leq n$$

N is the number of possible times, 24.

$$\sum_{k=1}^{24} \frac{24!}{k!(24-k)!} = 16,777,215\ possible\ unique\ combinations$$

With over 16 million possible choices, with multiple evaluation criteria, a manual examination was excluded.
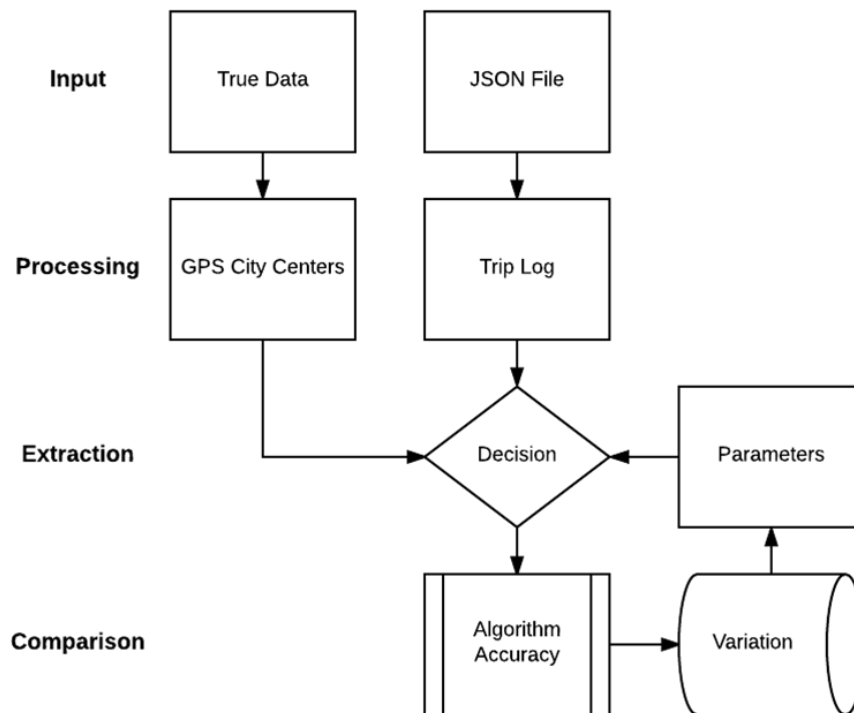

Figure 1: Long Distance Travel Data Extraction Methodology

Input: The participant's JSON file of GPS data collected by Moves and exported during the exit interview is inputted into the model.

True Data: During each participant interview, an Excel file was generated with each date that the participant was involved in the study. This file was then populated with dated origins and destinations of long distance trips that the participant took during their involvement in the study. The City and State name are listed for each trip in the US. For each trip outside the US, City and Country name was used.

Processing: Trip Log: A 24-hour Trip Log was generated from the JSON File, with each GPS point collected during the study having a dated timestamp.

GPS City Center: The True Data city names were converted into City Center GPS points using the Python library, GeoPy.

Parameters were used to determine exactly what was extracted. A variable stating at what point(s) each day to extract data was implemented. These points are 1-24 hourly marks that return the next available data point for that subject. A pareto-optimal solution is one that optimizes possible outcomes in a multi-objective problem, finding the best overall solutions (Deb, Agrawal et al. 2002). In this case, optimal meant maximizing the percentage of captured trips, while minimizing the data points used. Rather than attempt to test each possible solution by hand, evolutionary algorithms were employed to find the optimal time of day, and number of points used each day, to accurately retrieve LDT origins and destinations. 100 tests were run using the multi-objective evolutionary algorithm (MOEA), non-dominated sorting genetic algorithm II (NSGA-II) (Deb, Agrawal et al. 2002). The accuracy of trip detection served as the factor of fitness for each candidate, allowing for it to dominate, or be dominated by each other candidate.

For each trip, if an origin or destination is present in both the True Data and the Trip Log it is marked as recorded. A variable buffer between the True origin and destination, and the Trip Log's returned locations was used to determine how accurate the City Center GPS locations were at capturing actual travel locations. The Trip log sometimes varies by up to 24 hours compared with the True Data based on the time that the trip was taken, and when the data is collected based on the input parameters. If both the origin and destination are correct for a trip, that trip is counted as a correctly identified trip. The greater the percentage of trips returned by a candidate, the higher the score that it was assigned.

Variation within candidates is maintained by using evolution methods within offspring creation. Both crossover and mutation methods were implemented in this instance. Crossover divides successful candidates into pieces and combines these pieces with other successful candidates to generate offspring. Mutation creates slight adjustments within successful candidates to test for improved accuracy.

In this way, we were able to determine the maximum accuracy possible to be obtained from the dataset. Additionally, we were able to find the best times of day to collect data; depending on how many points you were hoping to collect. Finally, we were able to examine diminishing returns and suggest a number of points that optimize number of check-ins and accuracy and evaluate this process at determining precise trip ends.
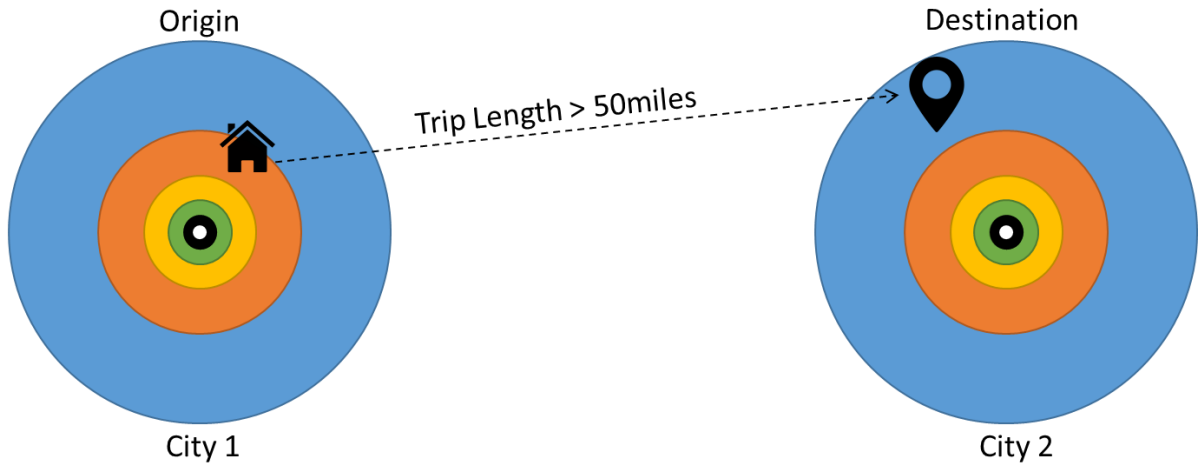
Figure 2: Trip selection visualization with city buffers.

Data was extracted from the GPS dataset at the start of each hour in varying degrees to determine optimal times to check-in. Accuracy of this method was determined in two ways:

- The ability for a non-generic sorting algorithm to determine optimal times, frequencies, and buffer distances to extract trip origins and destinations.
- The ability for extracted data points to represent LDT mileage.

Accuracy of each candidate was determined by examining the data for long distance trip origins and destinations collected. A candidate received a score of 100% if no long distance trips were missed.

A distance buffer was created surrounding each City Center GPS location to accommodate for the lack of exact location reporting in interviews. It should be noted that while the city center provides a good reference point for participant travel, it does not directly represent user behavior during the study. Thus a buffer was applied to this centroid in the hopes of better capturing participant movement. Evaluation was originally run using the ability of the test to return correct trip origins and destinations with 6 different distance buffers: 50, 25, 10, 5, 2, and 1-mile radii from city centers. The maximum buffer implemented was 50 miles, the largest value allowable based on the minimum distance we allowed to categorize long distance travel. Any buffer larger than that might categorize the origin as the destination for trips nearing 50 miles.

4. Results

As this buffer was expanded, greater results were returned. The largest buffer accurately matched GPS trip origins and destinations within 50 miles of the True Trip origins and destinations for 91% of the long distance trips made. Decreasing this buffer to 25 and 10 miles reduced the accuracy negligibly (91 and 89% respectively), but provided much more specific information about the users location. When this distance was reduced to a 5-mile radius from the city centroid, the algorithm was only able to accurately return 80% of the trips taken. With a 1-mile buffer, 55% of all trips were accurately returned. At the maximum buffer distance, 50 miles, accuracy reached 92% of all long distance trips' origins and destinations captured, using 8 data points. By decreasing this buffer to 25 miles, only 89% of trips' origins and destinations were correctly accounted for, but with much greater detail as to where the participant was.
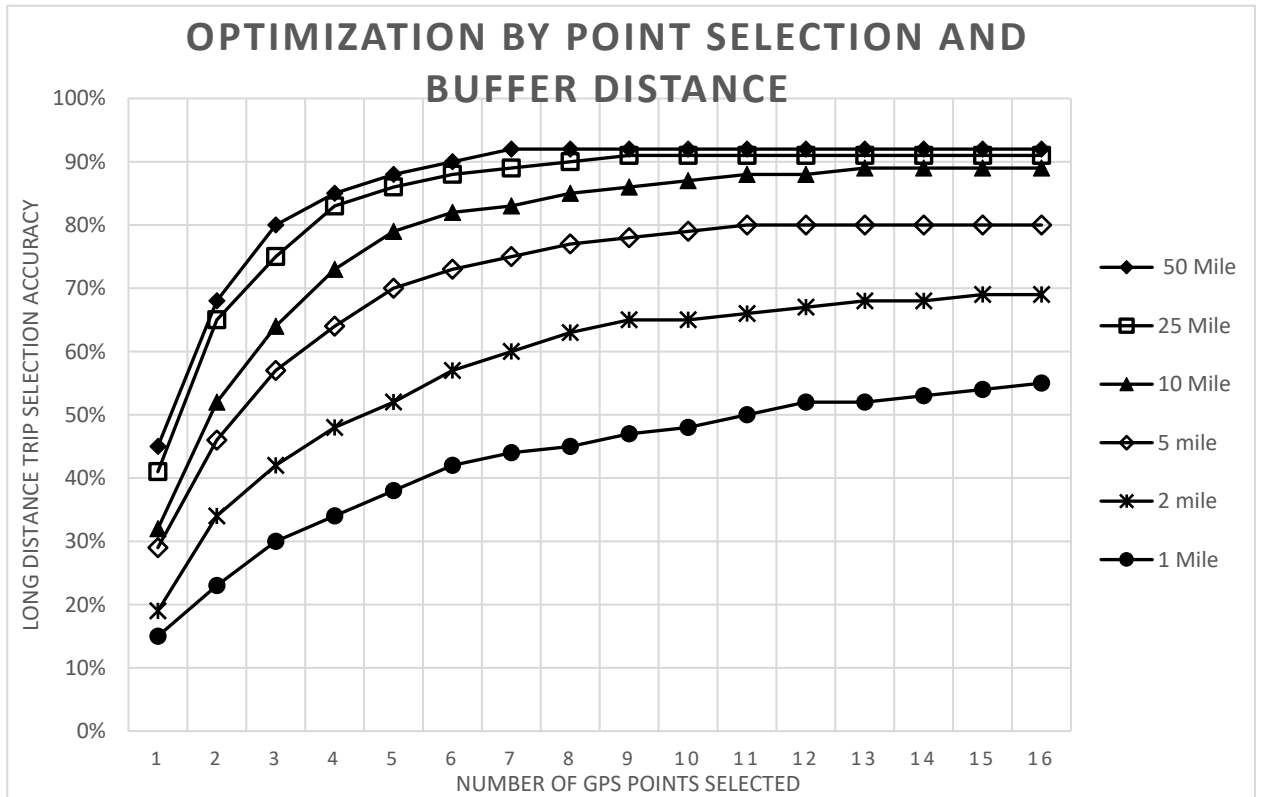

Figure 3: Graph of diminishing returns of additional points on accuracy of long distance travel data collection.

Each distance buffer expressed diminishing returns based on number of points used. The first optimal time for collection in each distance held between 49% and 26% of the correct data for that test. As the distance buffer reduced in size the first data point held less of the total accuracy. In the least specific test, using a 50-mile buffer, the first four data points held 92% of the correct data in the trial. In comparison, the 1-mile buffer test required 11 data points to return 92% of the total data collection, with the first data point only returning 27% of the correct results.
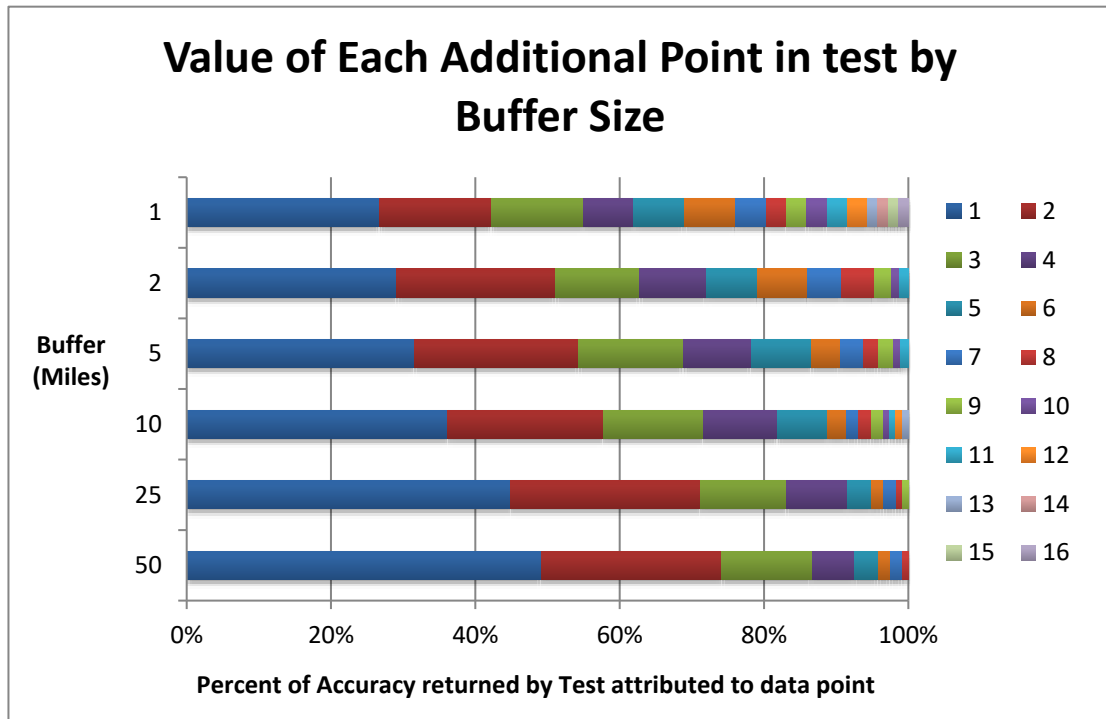

Figure 4: Value of each additional point in total accuracy return by buffer size

4.1. Hours of Importance

The single hour of greatest importance for each test was inconsistent. Four of the buffer distances, 25, 10, 5, and 2 miles each found the most accuracy for a single point by extracting data at 9am. The hour of 3am tied with 9am for two-mile accuracy, and was the most accurate for one-mile accuracy. Each test returned an early morning hour and a late morning hour as the two points to be used for greatest accuracy. The first circumstance where a time after noon was used was for the three-point accuracy at five-mile buffers. Even when using five points, the majority of the data takes place in the morning, with only one extraction point coming after noon in any trial. Unsurprisingly, there was no consistent answer for the most accurate times of day across distance buffers.

While some might expect extraction throughout the day to return the best results, these tests show that this is not true. Using a 50-mile buffer, 80% of all trips can be caught using only three times, 4am, 7am, and 9am, potentially representing times when users were likely to be sleeping and therefore having completed their travel. While the 50-mile buffer returned 92% of all trips, that 8% is still unaccounted for. More research must be done to determine the characteristics of these missed trips. They could be due to lack of phones being turned on, incorrect recall in the interview phase, or errors within the software.

5. Conclusions

This study concluded that even with high levels of data collection, phones do not return 100% of long distance trips. However, they demonstrate a viable means of capturing relatively high proportions of travel with minimal respondent burden. In travel surveys, long distance travelers have a tendency to forget trips and misrepresent mileage travelled. The methods developed show that LDT mileage can be approximated with a reduced amount of data collected from a passive mobile phone GPS tracking application. The study was unable to account for all long distance trips taken, most likely due to factors such as a lack of phones being turned on to collect data throughout the study period, incorrect interview response data due to incorrect memories or lack of information by the participant, and errors by the phone app in returning correct data.

This study found that it is possible to use only a single point per day (83% accuracy) to estimate LDT behavior with larger buffer distances, greater accuracy in results were found as more data was used. Maximum accuracy was achieved using 12 points per day. Future improvements to the study could involve the propensity for participants to travel certain distances based on their origin, mode of travel, or demographic profile.

It should be recognized that the sample used was mostly white, male, college-aged, middle-class and somewhat tech savvy, from North America. This sample was very useful for the purposes of this study, in likely having high levels of recall of trips. Testing is needed to determine suitability of similar approaches and methods with broader populations, especially for other applications. Other limitations include that participants sometimes provided responses that did not correctly locate their exact location; such as if someone visited a suburb of a city but was unaware that their destination was not within the city limits. Sometimes, the phone track would place the participant in a location that they most likely did not travel to, most noticeably during flight. In future, developing methods to isolate and remove such records would be a helpful step to improve accuracy.

This research approach, which embraces the emergent field of passive data collection in transportation, opens up a number of possible LDT applications. The most obvious is in developing demand estimations for LDT, for key regions and networks. Opportunities also exist to integrate these methods into research on freight and logistics, including both land-based and maritime movements. If we could get large proportions of truck drivers in a state or nation to install such an app, one may be able to get a very rich picture of freight movements, without the expense or difficulties in obtaining proprietary vehicle movement data. The approach to reduced frequency of GPS locations could particularly help with modelling ship movements. The app platform itself offers significant potential to combine activity logging with other research methods, including triggering requests for user input (i.e. surveys) when particular patterns of behavior are recorded. Where the app is supplemented with surveys that are only provided when a user has travelled to a destination more than 50 miles from their origin (as the research team has proven possible) such methods could be used for heavy vehicle road safety research on issues such as fatigue management. The potential to do on-arrival, at-destination tourism surveys triggered only when someone has travelled a certain distance from home is also an enticing prospect, so as to capture real-time tourist experiences. These would be particularly useful in studying tourist dispersal (movement beyond ports-of-entry and away from tourist hot-spots) capturing both visitor's travel behavior and via survey their expenditures, which are a major concern for that field of research. Expanding sample sizes should not be too difficult given the ease of use of the technology, low respondent burden and low data collection costs.

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