INNOVATIVE PROCEDURES FOR TRAVEL DATA COLLECTION AND PROCESSING

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Statement

In this thesis, some contents are from my papers published during my PhD study. My contributions to these papers are all over 80%, as compared to the co-authors. These publications are:

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GLOSSARY OF TERMS AND ABBREVIATIONS

BBN: Bayesian Belief Network

CAPI: Computer-Assisted Personal Interview

CASI: Computer-Assisted Self Interview

CATI: Computer-Assisted Telephone Interview

CBD: Central Business District

DFA: Discriminant Function Analysis

GIS: Geographic Information System

GPS: Global Positioning System

HDOP: Horizontal Dilution of Precision

ITLS: Institute of Logistics and Transport Studies (University of Sydney)

K-S Test: Kolmogorov Smirnov Test

MD: Mode Detection

NHTS: National Household Travel Survey

NN: Neural Network

NSW: New South Wales

OSM: OpenStreetMap

PALMS: Personal Activity and Location Measurement System

PDA: Personal Data Assistant

PI: Purpose Imputation

PR: Prompted Recall

SI: Segment Identification

TDX: Transport Data Exchange

TI: Trip Identification

UTC: Universal Coordinated Time

VKT: Vehicle Kilometres Travelled

ABSTRACT

Global Positioning System (GPS) or Smartphone technology has been increasingly used in travel data collection. Although GPS devices can directly record spatial and temporal information, trip ends, travel modes and trip purposes are not recorded. So GPS data processing becomes a critical procedure to produce these results, which can be used in transport planning. It has been proved that GPS records are more reliable than travel diaries; however, the quality of GPS data processing work usually influences the quality of results. Researchers have been engaging in the improvement of GPS data processing for the past decade. Traditionally, data processing for GPS records (from dedicated GPS loggers and Smartphones) includes three steps, namely trip identification, mode detection and purpose imputation. However, the results of mode and purpose detection are entirely based on the result of trip identification. Hence, the total accuracy of a GPS survey would be the product of the accuracy of each step.

This thesis focuses on the improvement of travel data quality by improving data collection and processing. In this study, a new procedure is introduced which combines the process of trip identification and mode detection. Some general rules (i.e., a threshold of dwell time and the time interval for recording data) are tested. This research also firstly applies a new technology, a life-logging camera, to travel data collection. Images are used to help to pursue ground truth -- especially recorded trips in which GPS data were missing -- and detect some types of travel modes in order to improve the accuracy of data processing. An automating image processing procedure is proposed and tested in this study. In addition, a concept of "mode-point-chain" is discussed to identify the cases of mode change and modify incorrect mode detection results. For the process of purpose imputation, more travel information is suggested to be used in the process. This thesis also uses tour-based information in trip purpose imputation to improve the results. By using the new procedure, the trip identification accuracy was increased by almost 30 percent, taking the missing trips into

account. Since trip identification and mode detection were combined, this increase also benefits mode detection results. With the help of image processing and the new procedure of mode change detection, the accuracy of mode detection increased by 7% regardless of the accuracy increase in trip identification. The new processing method also increased the accuracy of trip purpose imputation by 8%. This improvement can help researchers and planners obtain more accurate data for decision making and planning.

1 INTRODUCTION

This thesis reports on a new method of travel data collection and a corresponding procedure for data processing by using Global Positioning System (GPS) devices and life-logging cameras based on data collected in Sydney (Australia), Oxford (UK), and Cincinnati (USA). In the first chapter, Section 1.1 briefly introduces the background of the research topic. A few research questions are identified in Section 1.2 to show the motivation of this study. Section 1.3 highlights the contribution of this thesis to the field of passive travel surveys and travel data processing. In Section 1.4, an outline of the thesis is presented to show the structure of the whole thesis.

1.1 BACKGROUND

Data collection is a critical procedure for all transport research. The household travel survey is one of the critical surveys that obtains information regarding individual travel behaviour. The information usually includes socio-demographic data, household size and structure, and all the journeys and activities that people make on given days, etc. In terms of journeys, not only is the spatial and temporal information for origins and destinations collected in the survey, but also the choices of travel mode and the types of trip purposes are reported or recorded for transport planning and decision making. These types of information can enhance research or modelling to forecast changes in travel patterns, transport facilities, and policies based on social and economic change and development. The models established for transport planning and policy making rely heavily on the quality of data collected. Two factors impact the quality of a survey, data quality (i.e., the accuracy and relevance of the data collected) and the representativeness of the survey.

Over the past 60 years, researchers have been making efforts to improve travel survey methods, so as to impact data quality and response rates, and reduce the survey costs at the same time. At the very beginning of collecting travel information in the 1950s, a face-to-face interview was usually conducted and is still used in many countries as the principal survey method (Wolf, 2000), After that, there has been a new approach that people attempted to apply about every decade (Tsui, 2005; Stopher, 2008). Generally, travel surveys have developed from self-reported surveys to passive surveys. Traditionally, no matter what method or medium (e.g., paper and pencil, mail, telephone, internet, etc.) they use, people need to report their travel information in a travel diary by themselves. It has been shown that a self-report survey not only reports inaccurate information, but has a relatively high non-response rate. About 18 years ago, the development of a new technology, GPS, provided an opportunity for passive data collection.

The Global Positioning System (GPS) is a satellite-based navigation system, which can offer information about where people or vehicles are at a certain time. It can also provide the route and speed of the travel. The system has been widely used in military, civil, and commercial applications around the world.

The GPS survey was then introduced to support or even replace travel diaries to record people's travel information due to the lack of accuracy of the diary survey. The GPS survey also collects similar information that people report in travel diaries. However, for some important information, e.g., travel modes and trip purposes, GPS devices cannot directly and automatically record it. Therefore, a process of information imputation is required. Over the past decade, researchers have focused on the approaches of processing GPS data, including the data from dedicated GPS devices and Smartphones, to improve the accuracy of imputation. To provide the data required in travel surveys, GPS data processing typically includes trip identification, travel mode detection and trip purpose imputation. Although advanced approaches have reached a high level of accuracy in terms of identifying trip ends and travel modes, the quality of GPS surveys still suffer from the signal issue, which leads to missing data.

1.2 RESEARCH QUESTIONS

For the past decade, GPS devices and Smartphones have become popular in travel surveys. However, there are a number of research gaps existing in data processing. The first issue is signal noise and signal loss from GPS or Smartphone data. It is common that there would be some spurious GPS data points (i.e., signal noise) and some data gaps (i.e., missing data) due to insufficient satellites to obtain positions or obtain a correct position, or urban canyons or cold starts (see more details in Section 2.2). These issues cannot simply be solved by applying a new processing method, because no method can process data that were not recorded by the devices. According to the history of travel surveys, there might be a new method that can change the way of collecting travel data. This study addresses this gap by introducing a new technology into travel data collection.

The second issue is that the detection of mode and purpose is based on the result of trip identification in the current processing methods. If the result of trip identification is poor, mode detection and purpose imputation also cannot produce a correct output. This thesis examines this gap to see if the whole procedure of GPS data processing might be changed. Another gap is regarding "ground truth" for GPS research. Generally, the term "ground truth" is related to measurements in cartography, where data collected remotely (e.g., by satellites) are validated by measurements made on the ground. In travel data collection in transport research, ground truth refers to what the traveller really did (e.g., travel time and distance, trip ends, travel modes, trip purposes, etc.). There is very little research that has addressed this issue. Although researchers usually use various data sources (e.g., prompted recall surveys) as ground truth, these data sources also have errors. A Prompted Recall (PR) survey is conducted after the main survey, in which respondents are assisted to recall their actual travel by receiving GPS-generated maps of where and when they travelled. This study introduces a new approach to obtain ground truth. In addition, the methods of mode detection and purpose imputation still have potential to be improved. More details of research gaps are discussed in Chapter 2.

In order to address these gaps, a main research question of this thesis is:

> *"To what extent can new and enhanced technologies/methods further improve the data quality and the accuracy of detection?"*

Before answering this, a number of sub-questions are also necessary to be mentioned:

- What might be the best travel data collection method in the next ten years?
- How could the whole GPS data processing procedure be improved?
- If new technologies will be applied in data collection, how would the new data be processed?
- Should a GPS device still be used for travel data collection?

In addition to putting more effort into improvement of GPS data processing procedures, this thesis also explores changes of lifestyle and the development of new technologies, and introduces life-logging cameras in travel surveys. The performance of the new devices is also investigated. Applying a new device or method to collect data will always be a challenge. The assessment of current collection methods has been undertaken in the literature, so it is necessary to compare the new method with current collection methods to test the advantages of a new method, and the feasibility of applying it. Similar to the beginning of GPS applications, a new technology or a new device requires a new approach to process the data from the device. Because a travel survey involves a large amount of data, automating the processing work is important and required.

1.3 THESIS CONTRIBUTION TO THE LITERATURE

The field of travel data processing, especially for GPS data, has been developing rapidly; however, some research gaps still exist. There is no standard procedure for GPS data processing and there is no evidence proving which method currently used is superior to others. This thesis introduces a new device along with the GPS device to collect travel data. Also, a corresponding procedure for travel data processing is developed to fill the research gaps that currently exist and to illustrate the new method's superiority to other methods.

In terms of the use of data, the life-logging camera is applied in this area for the first time. The passive camera has been used in research for only a few years, mainly in physical activity studies. Because visual content can provide sufficient useful information for mode and purpose detection, and the photos are not subject to the signal issues, this is a promising technology.

Another contribution that the life-logging camera can make is to find “ground truth”. Most current research uses Prompted Recall (PR) survey data as “ground truth” to check the accuracy of the GPS survey and processing. However, PR data also have similar problems to self-reported surveys. It is ground-breaking work to coordinate/compare images with GPS data for acquisition of better “ground truth” data.

In the steps of trip/segment identification (TI/SI) and mode detection, this thesis introduces a new approach which combines these two separate steps. There is no research that has been conducted combining these two steps. Since speed change is detected in TI/SI, it is inefficient to analyse it again in mode detection; therefore, mode detection can be combined with TI/SI, which shortens the processing time. It also enables mode detection to be less dependent on TI/SI. In this approach, the rules for determining segments are first tested with empirical and/or theoretical research. The time interval for GPS devices to record reliable data is also tested for the first time. Moreover, signal noise has significant negative influences on the detection results. Some researchers ignore this problem, resulting in unreliable results, while some researchers take a great amount of time on “map editing”, a post-validation step to deal with signal noise and signal loss. This thesis discusses a new method of map editing, significantly reducing the processing time. By using the life-logging cameras, the other main problem of GPS data, i.e., signal loss, can be tackled. Image processing for mode detection is another original contribution of this study. Although image processing has been used in the recognition of faces, vehicle plates, etc., images are adopted in the detection of travel mode for the first time.

In the step of trip purpose imputation, the input variables currently used are not sufficient. The accuracy of trip purpose imputation based on current methods is much lower than the accuracy of mode detection. This study suggests some additional information as inputs for the imputation. In addition, tour-based information is applied to assist trip purpose detection for the first time. Most current research to automate mode and purpose detection is based on trips/segments. Each of these trips/segments is regarded as a single, separate object when detecting the modes and purposes. However, in reality, there are actually some sequences when people travel. Tour-based information is tested and then applied in this study for the first time.

1.4 Summary and Thesis Outline

This thesis includes five chapters. Chapter 1 discusses the background to the research, introducing a brief history of travel surveys. This chapter also introduces the motivation of studying this topic by presenting the main contributions to the area of travel data collection. The key points of this chapter are:

- GPS/Smartphone survey is used as a state-of-the-art method in travel survey method.
- The main research question of this thesis is: "to what extent can new and enhanced technologies/methods further improve the data quality and the accuracy of detection?"
- This study will contribute to GPS/Smartphone survey methods by improving the data processing procedure from data collection to producing results for transport planning and travel demand modelling.

The content of the remaining chapters is set out in the following paragraphs.

Chapter 2 reviews all the methods of travel data collection from the 1950s to the early 21st century. First, some traditional methods, e.g., face-to-face interviews, mail surveys, telephone surveys, etc., are discussed, showing the development of travel data collection and the motivations to change the methods. The GPS survey is then explored. A systematic review of GPS surveys conducted around the world shows the popularity of using GPS devices or Smartphones to collect data. Also, different data processing methods are compared in detail. Although all the methods are not based on the same dataset, there are some common aspects that can be compared. In addition, the technology of the life-logging camera is introduced. Chapter 2 lists a number of applications of life-logging cameras.

Chapter 3 presents the framework of a new method that collects travel data and processes the data. The rule for identifying trip ends and the interval of recording GPS data are tested, to improve the performance of trip identification and reduce the processing time. The new combined procedure of trip identification and mode detection is discussed based on GPS devices and life-logging cameras. The procedure includes the identification of trip ends, mode change, and different travel modes. Walk and train trips are detected by GPS devices based on the general GPS information and the GIS information obtained externally. Car and bicycle trips are detected by life-logging cameras because the critical features for these two modes can be easily captured by image processing. Because the shapes of critical features for car and bicycle are identical, a Hough transform is adopted as the method for detecting these two modes. This new framework also applies photos from life-logging cameras to locate and identify the missing trips, which is much more reliable than the map editing process. The cost of the map editing process is also much higher than image processing, so the new framework can reduce the data processing cost compared to existing methods. In terms of purpose imputation, new rules of inputting additional travel information and tour-based information based on GPS data are discussed.

Chapter 4 analyses the issues mentioned in Chapter 3 and shows the results and findings based on the framework suggested in Chapter 3. The chapter starts from some tests of general issues in GPS surveys. A reasonable interval for recording GPS data and a threshold of dwell time for determining a stop are suggested. The data collected in Oxford, UK are used for the test. The performance of the new procedure is demonstrated step by step from segmenting the raw data to final results of trip identification and mode detection. The data collected in Sydney, Australia is applied as a case study. In Chapter 4, a comparison is undertaken between the results of the new procedure and ground truth to show the accuracy of the processing work. Another comparison between the results of the new procedure and the existing procedure for processing travel data is also conducted to show the accuracy improvements made by the new procedure. A case study from the GPS survey in the Greater Cincinnati region, USA shows the performance of the new rules applied in purpose imputation.

Chapter 5 summarises all the findings and analyses in this thesis, and also highlights the contributions of this thesis to the literature. Limitations of this study are discussed in this chapter, followed by further discussions on this topic. Introducing cameras into travel data collection might be controversial as it may cause a privacy issue. The way to cope with the ethical issues arising is suggested.

2 LITERATURE REVIEW

Travel surveys are widely used around the world for transport planning. Traditionally, the face-to-face interview was the first approach used in travel surveys in the 1950s. Due to both safety and cost issues, other approaches, such as mail-out/mail-back and the telephone survey, gradually replaced face-to-face interviews by the 1970s in the US, although face-to-face and other survey methods have continued in other countries around the world. In the late 1990s, Global Positioning System (GPS) devices started to be introduced in travel surveys and have been developed rapidly over the past decade. Because GPS devices are very accurate at recording time and positional characteristics of travel, GPS surveys can improve the accuracy and depth of travel survey data, and correct the trip misreporting issue caused by respondents. Compared with GPS records, paper-based travel diaries under-report about 20-30% of trips (Wolf, 2000; Bricka and Bhat, 2006; Stopher and Greaves, 2009; Stopher and Shen, 2011). However, as a new method, the GPS survey also has some shortcomings, such as unstable signal acquisition in certain areas and difficulties in GPS data processing.

In this section, an overview of travel surveys, especially GPS surveys, is provided. In Section 2.1, the history of travel surveys from face-to-face interviews to GPS surveys is reviewed, showing the development of travel surveys. Section 2.2 discusses GPS surveys specifically in different countries. The initial idea of using GPS surveys in transport data collection was to replace paper-based travel diaries; GPS surveys currently are being applied in a number of transport fields. Some of these applications are introduced. The methods of processing GPS data are reviewed and compared in Section 2.3. Section 2.4 introduces a new technology that potentially could be used in travel surveys. Section 2.4 suggests current research gaps, which leads to the research goals and hypotheses for the next chapter.

2.1 TRADITIONAL TRAVEL SURVEY METHODS

The role of the travel survey (i.e., travel diaries) is to collect detailed travel and activity information from respondents, and then use the collected information in travel demand modelling (Arentze et al., 2001). In the field of urban transport planning and modelling, the household travel survey started as a face-to-face interview in the 1950s in the US, in which interviewers visited the participants' homes and asked questions about the household's travel information. The interviewers recorded the answers using paper and pencil. However, this method was considered to be unsafe in some areas in the US and the labour and time costs for interviews were too high. Therefore, interviews were gradually replaced by the mail-out/mail-back survey, which is another method started in the 1960s in the US (Wolf, 2000), in which households received some survey documents by mail and returned them after completing the survey. The main problem of a postal survey is the low response rate. In addition, the mail survey still needs labour to transfer the records from paper to computers.

In order to overcome the disadvantages of paper-and-pencil surveys, computer assisted surveys were introduced in the 1980s. There are three main types of computer-assisted survey — the computer-assisted telephone interview (CATI), the computer-assisted personal interview (CAPI), and the computer-assisted self-interview (CASI) (Stopher, 2008). The web survey is one of the CASI methods. Respondents can fill in the travel information in a web interface. In the web survey, some information, such as travel modes and trip purposes, can be chosen from a list, while other information, such as start and end times for a trip and addresses of origins and destinations, must be typed in by the respondent. However, all of these methods face issues of non-response (Zimowski et al., 1997) and misreporting (Wolf, 2000). Therefore, automated data collection methods were then considered.

2.2 GPS TRAVEL SURVEYS

GPS technology has been used in travel surveys since the late 1990s (Wagner, 1997). Most GPS surveys were undertaken as supplementary surveys to measure the accuracy of traditional surveys. Due to issues of non-response and data inaccuracy in traditional survey methods, GPS technology provides the potential to replace the traditional travel survey and obtain more reliable and accurate data. Although GPS devices are very accurate at recording time and positional characteristics of travel, they cannot record travel mode, trip purpose or the number of occupants in a private vehicle – all of which are important attributes that are collected in a traditional travel survey. Therefore, data processing procedures become critical to the usefulness of GPS surveys, because there would be insufficient information for travel modelling purposes without the results of the processing.

For the past decade, GPS surveys have been undertaken in Australia, Austria, Canada, China, Demark, France, Israel, Netherlands, Japan, Sweden, Switzerland, the UK and the US (Schönfelder et al., 2002; Itsubo, 2006; Oliveira et al., 2006; Marchal et al., 2008; Bohte and Maat, 2009; Krygsman and Nel, 2009; Papinski et al., 2009; Schüssler and Axhausen, 2009; Stopher and Wargelin, 2010; Beijing Municipal Committee of Transportation, 2012; Kelly et al., 2013; Kohla and Meschik, 2013; Rasmussen et al., 2013; Stopher et al., 2013a;) at least. Some countries have conducted a number of GPS studies, but Table 2.1 only shows some representative examples of GPS surveys around the world. From these surveys, researchers reported that GPS devices can correct the trip misreporting issue caused by respondents and improve the accuracy of travel data (Bricka et al., 2009). The earliest GPS surveys required participants to enter additional trip information into a personal data assistant (PDA) when each trip started. However, this step increases the complexity and cost of the GPS survey (Bachu et al., 2001). Since researchers improved the methods of processing GPS data, the PDAs have no longer been used.

Table 2.1 GPS Surveys Conducted in the World

Location	Year	Survey purpose	Device	Sample Size	Collection period	Technical details	Processing involved*
Four states in Australia	2007-2013	Travel behaviour change monitoring	Dedicated GPS device, recording data every second	130 households	15 days (6 waves)	Random sampling; GPS-only survey	TI, MD
Ontario, Canada	2007	Route choice	Smartphone plus a GPS receiver	31 respondents	2 days	Snowball sampling; GPS survey with a pre-interview and a web-based prompted recall survey	TI, PI
France	2007-2008	Sub-sample of National Travel Surveys	Dedicated GPS device, recording data every 10 seconds	9% of the main survey	7 days	Random sampling; GPS survey with one day travel diary	TI, MD, PI
Matsuyama, Japan	2004	Compare GPS records and travel diaries	GPS-equipped mobile phone, recording data every 30 seconds	31 respondents	5 days	Non-random sampling; paper-based diary and GPS survey with a web diary	TI
Jerusalem, Israel	2010	GPS-only household travel survey	Dedicated GPS device, recording data every second	3000 households	1 day	Random sampling; GPS-only with a prompted recall survey	TI, MD, PI
Three cities in Netherlands	2007	Residential selection	Dedicated GPS device, recording data every 6 seconds	1104 respondents	7 days	Random sampling; GPS-only survey with a web-based prompted recall survey	TI, MD, PI
Western Cape, South Africa	2008	Assess the reliability of GPS survey	Dedicated GPS device, recording data every second	100 respondents	14 days	Random sampling; GPS survey with two-day travel diary	TI, MD, PI
Borlänge, Sweden	1999-2001	Traffic safety	In-vehicle GPS device, recording data every second	310 vehicles	15 days-243 days	Stratified Sampling; in-vehicle GPS survey	TI, PI
Three cities in Switzerland	2008	Explore whether participants pass certain billboards	Dedicated GPS device	4882 respondents	average 6.6 days	Random sampling; GPS-only survey	TI, MD, PI
UK	2011	Test the possibility of replacing travel diaries	Accelerometer-equipped GPS units, recording data every second	429 households	7 days	Random sampling; pilot survey (GPS only) for National Travel Surveys	TI, MD
Ohio, US	2009-2010	GPS-only household travel survey	Dedicated GPS device, recording data every second	2059 households	3 days	Random sampling; GPS-only survey with a web-based prompted recall survey	TI, MD, PI
Graz and Tullnerfeld, Austria	2009-2010	Test an integration of new technologies for a mobility survey	Dedicated GPS device	235 respondents	3 days	Random sampling for four groups (passive GPS-only, active GPS-only, GPS with diary, and diary-only; pilot GPS survey with prompted recall	TI, MD, PI
Beijing, China	2010	Sub-sample of Beijing Household Travel Surveys	Dedicated GPS device, recording data every 5 seconds	890 persons	1 day	Random sampling; GPS survey with one day travel diary	TI, MD
Greater Copenhagen Area	2013	Part of the research on travel chain and sustainable mobility	Dedicated GPS device recording data every one second	54 households	3-5 days	Random sampling from Danish National Travel Survey; GPS survey with one day travel diary	TI, MD

*TI =trip identification, MD= mode detection, PI= purpose imputation

From the beginning of the 21st century, prompted recall (PR) surveys have been conducted, in which respondents are assisted to recall their actual travel by receiving GPS-generated maps of where and when they travelled. PR surveys are used to validate the GPS data, because GPS devices are also subject to some problems such as difficulty in obtaining a signal in certain areas and devices being left at home, which means that GPS would miss data that need to be collected.

Bachu et al. (2001) undertook a proof-of-concept experiment with a PR survey. This survey was a face-to-face interview in which respondents reported their trip purposes and vehicle occupancy. Bachu et al. (2001) suggested that PR surveys could reduce burden on the respondent because it took only 15-20 percent of the time for completing a one-day diary, which results in a high response rate for PR surveys. They also found that even after 3-4 days, respondents still could recall their travel information in a PR survey.

Recently, PR surveys have been developed as web-based surveys and Smartphone-based surveys (Giaimo et al., 2010; Greaves et al., 2010; Dias, et al., 2014; Safi, H., 2014). In these surveys, respondents usually receive a map of one day's travel based on a Geographic Information System (GIS) application. They are asked to add more information or correct the GPS records in terms of travel modes, trip purpose, and vehicle occupancy. Some PR surveys even allow respondents to modify their trip information (e.g., changing trip route, inserting trips) (Greaves et al., 2010).

In a very recent study, Bricka et al. (2012) suggested that the GPS survey is more suitable for the younger respondent, while traditional survey methods may be better for older respondents, because younger respondents are more technology savvy. Another earlier study of the factors influencing response rates to GPS surveys by Hawkins and Stopher (2004) suggests that the acceptance/rejection rates of GPS surveys between the old and the young have no statistically significant differences. Different from Bricka et al.'s research, the method of recruitment of this survey in 2004 was a face-to-face interview. Even though the devices used in that survey were older generation devices, it still reached the conclusion that there is not sufficient evidence to show that the age of respondents significantly influences the acceptance of a GPS survey. This suggests that different methods for recruitment also may change the response rate for different ages.

It is widely accepted that GPS surveys can report more accurate data. However, signal loss and signal noise are the two main issues that GPS units have. Signal problems occur for several reasons, such as a cold start or warm start, which usually occurs at the beginning of each day (i.e., cold start) or when the GPS device switches from "sleep mode" to "working mode" after a person stops for one or two hours (i.e., warm start), and travelling in urban canyons. Urban canyons are formed by tall buildings flanking roads on both sides (Cui and Ge, 2003). Because the tall buildings can block the signal of satellites, they have impacts on GPS signal reception, and cause missing GPS data due to insufficient satellites. Also, signals may be reflected off the buildings, so that an incorrect position may be recorded by the GPS device. Signal problems result in missing trips or parts of trips and generating spurious trips (a sequence of points generated by a stationary GPS device that has been incorrectly identified as a trip). For those studies that require data integrity and identification of mode for each trip, such as physical activity or energy expenditure for the travelling task, the travel information for missing GPS trips becomes critically important. Although a number of studies (Tsui, 2005; Chen et al., 2010; Gong et al., 2012) have discussed the reasons for signal problems, only a few studies suggest how to fix the problem or reduce the errors that missing data would cause. Chen et al. (2010) used GPS to record data all day long without the "sleep mode" to solve the cold/warm start. This would increase the dataset size and reduce the working time of a device due to battery issues. The authors do not report the battery performance when they turned off the “sleep mode”. Also, they adopted detailed GIS information to deal with the issue of travelling in urban canyons. Stopher et al. (2013b) added an additional step, called “map editing” to fix some data errors manually. Even though there are a few approaches to overcome signal problems, missing data and errors are still the main challenges for GPS studies.

2.2.1 Smartphone-based GPS surveys

As Smartphones are becoming one of the necessities of daily life and a GPS module is usually built into Smartphones, Smartphone-based GPS surveys have been proposed to replace dedicated GPS devices (Gilani, 2005). Some research projects also use Smartphones to conduct surveys (Reddy et al., 2010; Hudson et al., 2012; Xiao et al., 2012; Bierlaire et al., 2013). Because Smartphones are now increasingly popular, using Smartphones to collect GPS data would reduce the costs. Also, most Smartphones have GPS and accelerometer sensors, both GPS and accelerometer data can be recorded by phones, and could be used to detect modes and purposes.

Although the Smartphone has less warm-up time to find the first position (Bierlaire et al., 2013), adoption of Smartphones as GPS devices in GPS surveys is limited by such issues as short battery life (compared with GPS devices), poor accuracy of positioning, and difficulties and high-cost of transferring data from phones to data centres (Safi et al., 2013).

2.2.2 GPS Survey Applications

Because GPS surveys have significant advantages as described above, they have been applied in a number of transport fields. Bullock et al. (2005) used GPS technology to measure whether a bus service was running on time. According to their conclusion, it is also shown that GPS is a cost-effective method to collect data. In addition, analysis of highway travel time and travel speed was undertaken by Quiroga and Bullock (1998). They concluded that GPS speeds determined from the latitude-longitude information were preferable for computing segment speeds.

Due to the advantage of GPS to objectively report the spatial locations, research on walking and cycling has also used GPS to provide better understanding of pedestrians and cyclists' behaviour. Menghini et al. (2009) specifically investigated cyclists' route choice by GPS data. They mentioned that, using GPS data, it is possible to estimate high quality route choice models.

Route choice, in fact, is one of the earliest fields to which GPS surveys were applied. Wolf et al. (1999) applied GPS surveys for route choice data collection, just a couple of years after GPS was introduced in household travel data collection to validate travel-demand models. GPS technology provides an opportunity to conduct revealed preference surveys for route choice research. The accuracy of trip identification and data integrity are often the most critical factors for route choice, because missing data could lead to inaccuracy of the results of route choice modelling. Papinski et al. (2009) recruited 31 individuals to carry GPS devices for their travel, and compared their planned routes and observed routes to understand the route choice decision-making process. In addition to the research on vehicles, the route choice of cyclists has become a hot topic. GPS can be used to test the preference of cyclists regarding bicycle facilities (e.g., paths, lanes, and boulevards). Generally, cyclists are more concerned with travel time and traffic volume, which are sometimes conflicting, because the shortest paths usually are arterial roads that have high traffic volumes (Dill and Gliebe, 2008; Broach et al., 2012.). Krizek et al. (2007) drew a similar conclusion, while they suggest that cyclists may not be deterred by intersections. Their conclusion also implies that land-use planning and transport policy for cycling could be adjusted according to the findings of route choice research.

Using GPS devices to assist an on-board survey is another GPS survey application (Oliveira and Casas, 2010). GPS was used to record the location of the participants and their arrival and departure times so that the boarding information, the routes of the trips, and transit trip times could be obtained more accurately.

GPS devices have also been applied in the health field to determine where physical activity happens (Rodriguez et al., 2005). Rodriguesz et al. (2005) combined GPS data with accelerometer data to observe the behaviour of transport-related physical activities. Krenn et al. (2011) reviewed several GPS applications in physical activity to determine the capability of GPS in research on the relationship between physical activity and the environment, and they concluded that GPS is a promising tool to obtain more reliable data. Mackett et al. (2006) conducted a survey using GPS and a diary especially for children to analyse their activities. University of California, San Diego has also endeavoured to develop a Personal Activity and Location Measurement System (PALMS, http://ucsd-palms-project.wikispaces.com/) to estimate Physical Activity Energy Expenditure by combining accelerometer data, heart rate monitor data, and GPS data.

Stopher et al. (2009) applied GPS travel surveys to evaluate travel behaviour change initiatives. They asked respondents over 14 to carry GPS devices for a week or 15 days for three waves (from 2005 to 2007). The evaluation was undertaken of a TravelSmart intervention in South Australia, which was an important element of the national program to reduce greenhouse gas emissions from cars. They also used GPS for this purpose in Canberra, and have recently completed a long-term evaluation over four states in Australia (Stopher et al., 2013a). More recently, they have undertaken a new study in northern Adelaide to evaluate another TravelSmart intervention from respondents' travel behaviour changes (e.g., changes in VKT (Vehicle Kilometres Travelled), switching mode from private vehicle to public transport, etc.).

2.3 GPS Data Processing

Typical GPS data processing can be divided into two principal steps. The first step is to transfer data from GPS devices to computers and create output files that could be used for statistical analysis. The second step is to identify trips and other information (e.g., travel modes and trip purposes). GPS devices can record the travel time and the coordinates of locations every second, which can therefore report start time and end time, and routes of the trips (Wolf, 2000). Speed is also accurately reported by GPS devices which is measured using a Doppler process. However, most GPS devices cannot automatically identify trip ends or report travel modes and trip purposes, although an in-vehicle device with no internal power supply can detect trip ends through the turning on and off of the ignition. Figure 2.1 shows a common procedure to process GPS data.

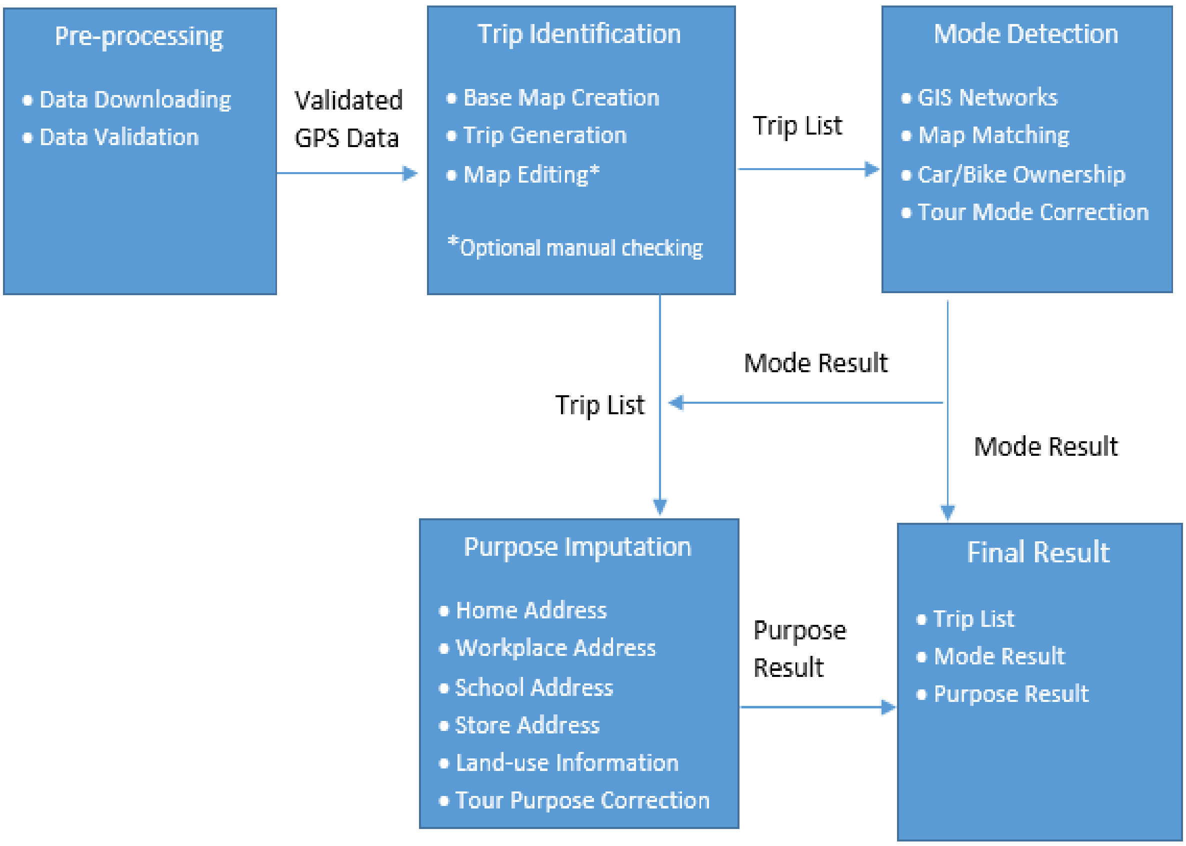


Figure 2.1 Process to Analyse GPS Data (Stopher et al. 2008)

Most research needs to process millions of data points, so looking for a potential way to reduce the number of data points becomes important. Although the latest computers have increased their capability, it still needs several days to process millions of data points from trip identification to mode and purpose detection. In practice, one second as the interval to record data is typically used, whilst 3 seconds, 5 seconds, or an even longer interval are also applied in some research. Reducing the number of data points by increasing the time interval of recording data can reduce the processing time and further reduce the data processing cost. (Note that using 3-second interval data would reduce the size of data sets by two-thirds, and 5-second data by 80 percent). Also, with the increasing use of smartphones in travel data collection, increasing the data recording interval could improve the performance of other devices (e.g., smartphones) to collect data. For instance, smartphones will have a longer battery life if a longer interval is used for recording data.

2.3.1 Trip/Segment Identification

Trip identification (TI) or segment identification (SI) would be the first challenge for all researchers. The travel-demand model needs information about each trip, and the following data processing (i.e., mode detection and trip purpose detection) is currently based on the results of trip identification. In this step, the concept *trip* refers to a one-mode trip, which is also known as a *segment*. There are also two common concepts, trip chains and tours, which are usually used by researchers. A trip chain means a journey between “significant” locations (e.g., home, workplace, etc.). It can show how people link their segments into journeys. A tour means a round trip from one place back to the same place. For instance, a home-based tour is a tour from home back to home with one or more stops away from home.

Currently, most researchers use rule-based algorithms to undertake the TI/SI processing. The early work of Wolf (2000) assumed that the dwell time between activities would be a main criterion for TI/SI. She suggested that 120 seconds of dwell time would be a reasonable time because the traffic signal cycle should always be less than 120 seconds according to the Highway Capacity Manual, and the signal light stops should not be regarded as trip ends. This rule has been widely accepted. Although other researchers provided some supplementary rules (e.g., Schüssler and Axhausen (2009) set point density as another criterion; Stopher et al. (2008b) adopted a rule of the latitude and longitude change), the 120-second rule is still being used in practice. However, the 120-second rule actually lacks empirical and/or theoretical research to support. Also some activities, such as pick-up/drop-off, may have a shorter duration. Therefore, it is reasonable to argue that the number of trips may be underestimated due to the excessive dwell time. Biljecki (2010) applied a two-step method to segment travel. The first step is to segment to *journeys* (between two meaningful locations), and then segment journeys to single-mode segments before detecting transport modes. He applied 12 seconds as a dwell time, which is much less than 120 seconds. However, this 12-second rule also lacks empirical research to support. With this rule, it generated excessive segments. As a result, some segments are merged after mode detection if the adjacent trips have the same mode classification results. This method may identify stops with short duration when people change mode, but it might also generate too many segments to merge, which will increase the processing time. Also, it could mistakenly merge two segments that have the same mode results but there actually is a real stop between them.

In the TI/SI procedure, besides identifying short stops, there are mainly two difficulties that need to be dealt with: signal loss and signal noise (Tsui, 2005; Biljecki, 2010). Based on the 120-second rule, Tsui (2005) analysed the cases of signal loss. Specifically, if the distance travelled based on the trip gap is less than 50 metres during the time of signal loss (i.e., longer than 120 seconds and shorter than 600 seconds), then there should be a short duration activity occurring in the time of signal loss; if the trip gap during this time is more than 500 metres, even if the signal loss time is longer than 120 seconds, then it is possibly an underground trip without a stop. Most TI/SI methods take the number of satellites and the horizontal dilution of precision (HDOP) into account to exclude signal noise. In general, this will delete only a few noisy data points. Spurious trips still exist in most research results.

All these methods use specific approaches for TI/SI, and the results of this step are used further for mode and purpose detection. In this case, mode and purpose detection would rely greatly on the reliability of TI/SI. Unfortunately, the results of TI/SI still have a great number of problems (e.g., spurious trips, missing trips, etc.).

2.3.2 Travel Mode Detection

Travel mode detection is the next data processing step. Similar to TI/SI, mode detection is usually based on rules. It is widely accepted that the main criteria for mode detection are travel speed, acceleration/deceleration and the information from the GIS database (Stopher et al., 2008b; Gilani, 2005; Bohte and Maat, 2009). Specifically, speed can distinguish most walk trips because they are made at speeds below 6 km/h and car trips, which are above 40 km/h, while acceleration/deceleration can be used to differentiate bicycle trips from walk trips and public transport trips from car trips (Stopher et al., 2008b). Public transport can also be easily detected by public transport timetables, and public transport routes and stops based on GIS databases. However, one still cannot be fully confident of the results because these deterministic methods struggle with the ambiguity of two similar modes, such as bicycle and bus. Stopher et al. (2008b) also suggested that household information could be used for the detection. For example, if the household does not own bicycles or cars, the mode they probably use would be public transport. This rule would be especially useful when it is difficult to distinguish bicycle trips, bus trips, or car trips only by speed. However, it cannot help to identify modes when respondents are passengers rather than drivers because people from other households could drive a respondent who does not own a car to a place. Comparing to data collected by a prompted recall survey, Stopher et al. (2008b) report that 95% of modes are correctly detected by their deterministic method.

By adopting GIS databases, map matching is another challenge especially for the situation where the quality of GPS data is poor. White et al. (2000) discuss some simple map matching algorithms to match inaccurate locational data with an inaccurate map/network. However, the match is usually somewhat uncertain. Bierlaire et al. (2013) used a more sophisticated probabilistic method based on a structural model and a measurement mode to match the GPS points and transport networks. They calculated the loglikelihood for all the possible routes, and the real path is assumed to be that with the highest log likelihood. The probabilistic approach not only provides more accurate map matching results, but also reduces the influences of GPS data errors.

Some researchers have adopted a probabilistic method to detect mode. Schüssler and Axhausen (2009) proposed a fuzzy-logic approach for mode detection. They set three fuzzy variables – the median of the speed distribution and the 95th percentiles of the speed and acceleration distributions. For the median speed, there were four membership functions (i.e., very low, low, medium, and high); and for the latter two variables, three membership functions were set (i.e., low, medium, and high). Based on the membership functions, each mode is given a probability. They did not report their accuracy of detection because there is no ground truth for them to compare against. As mentioned in Chapter 1, in travel data collection in transport research, ground truth refers to what the traveller really did (e.g., travel time and distance, trip ends, travel modes, trip purposes, etc.). The paper does not report the accuracy of detection, but the authors compared the trip distance and distribution for each mode between their results and the Swiss Microcensus on Travel Behaviour 2005 to evaluate the performance of their system in mode detection. They concluded that mode detection yields realistic results. Although researchers are becoming interested in accelerometers, and accelerometers have been proved helpful to identify trips and stops underground when the GPS signal is lost, it is still arguable whether accelerometer data should necessarily be used in mode detection. First of all, an accelerometer also has similar problems to GPS devices in distinguishing modes with similar accelerometer readings (e.g., trains and buses) (Stenneth et al., 2011). Also, accelerometer data are very sensitive to the location where people put the device/hold the device, especially for cycling due to movements of the cyclist's body (e.g., the accelerometer data would be very different if the respondent fastened the device on his or her arms or on their legs when they are cycling).

Biljecki (2010) designed a more sophisticated fuzzy expert system to classify more modes. He mentioned several indicators that might influence the output, such as speed, proximity to a network (e.g., railway, bus network, roads, etc.), water surfaces (for the detection of ferry), potential transition points (e.g., parking lots, bus stops, or train stations), acceleration, stop rate, heading change rate, elevation, journey distance, and journey duration. However, due to the lack of data and low performance of some indicators, he only chose mean speed, mean moving speed, nearly-maximum speed (i.e., 95^{th} percentile), proximity to the nearest network and the location of a segment with respect to a water surface as the inputs. He developed a fuzzy expert system that achieved 91.6% accuracy for ten modes determined by a prompted recall survey and the author's own experiments. Certainty factors are applied in his fuzzy system to measure the confidence of drawing a conclusion from the evidence. He also suggested that it still had much room for improvement, such as adding more inputs and removing noisy samples, e.g., a gap between two trips or a missing trip.

Due to the limitations of setting rules/algorithms for software, researchers have tried to apply new technologies in the transport area. Artificial Intelligence (AI), a learning system, has become possible to use in GPS data processing.

Gonzalez et al. (2010) applied neural networks (NNs) to deduce travel modes. They used mobile phones to record GPS data. As they mentioned, the advantage of using NNs is that they can explore the information from data that is missed by humans or other analysis algorithms. NNs need inputs and outputs to learn. In their research, the inputs they chose were acceleration, speed, estimated horizontal accuracy uncertainty, the percentage of location fixes that refer to the cellular signal coverage area instead of the GPS-calculated position of the phone, the standard deviation of distances between stop locations, and the average dwell time. The NN learnt the small differences between car, bus and walking trips based on the input attributes. After the training process, the NN was used to automatically determine the modes for new trips. Because neural networks perform better with more training data points, they trained the system 500 times and got a result with around 90% accuracy for detection of all modes determined from the data that people input. There are three main limitations of their research. First, the number of inputs for the neural networks might be insufficient. More inputs could possibly increase the accuracy of the NNs. Second, the sample size (i.e., 114 trips) or the amount of GPS data for the training is relatively small. These problems influenced their results and also limited their system to determining only three different modes. Third, the data they used are mobile phone data rather than dedicated GPS data, which have the problems of short battery life (compared with GPS devices), lack of multi-tasking, poor accuracy of positioning, and difficulties and high-cost of transferring data from phones to data centres. It should be noted that their accuracy of results are still not as high as those obtained with rule-based methods.

Tsui (2005) combined a fuzzy logic system with neural networks for mode detection. Her work was mainly based on the fuzzy system, while the values of parameters for membership functions of the fuzzy sets are determined by existing NN software, NEFCLASS-J, developed by the Technical University of Braunschweig. It can be improved by developing a dedicated NN system for GPS data processing. Her work identified modes correctly 94% of the time. However, the accuracy of the detection is calculated by comparing the GPS results with volunteers' travel diary results, which are not ground truth.

Similar to the above probabilistic methods, another method currently used in mode detection is Bayesian Belief Networks (BBNs). Feng and Timmermans (2012) adopted a BBN to detect modes based on both GPS data and accelerometer data. Due to the problem of recording speed (they were struggling with this manufacturing problem for their devices), they had to calculate average speed to define the real speed based on latitude and longitude information of each point. This decreases the accuracy of detection, because speed is one of the most important factors in the detection system. Moreover, the data are not rich enough (only 80,000 points) for detecting more than five modes. These records are not continuous segments in a whole day, which also simplifies the procedure. From their results, the model is excellent in most of the modes but train, and it also has some difficulties to identify a stop. It also cannot be concluded that this method is better at detecting modes than other methods.

Another current method to detect transport modes is Discriminant Function Analysis (DFA). Troped et al. (2008) conducted a survey requiring respondents to take GPS devices and accelerometers when they walk, run, cycle, in-line skate, or drive. Participants were asked to perform prescribed activities. In their analysis, they tested nine classification variables that could influence mode detection: means, medians, and inter-quartile ranges for accelerometer counts and steps, and GPS speed (calculated by using Doppler measurement). Modes were determined from the combinations of the nine variables. They do not provide more details of this method for the whole GPS data processing. From their results, the accuracy of mode detection using their approach is around 90%.

Reddy et al. (2010) conducted an experiment to ask 16 volunteers to carry six phones positioned in different places (e.g., positioned on the arm, waist, etc.) for 15 minutes for each mode. GIS information was not used in their research. They used a decision tree followed by a discrete Hidden Markov Model to detect modes and achieve 93.6% accuracy overall. Because it was based on an experiment, the quality of GPS data was better. Unfortunately, they did not test the method on a whole day survey in which signal problems would usually influence the quality of data and further reduce the accuracy of detection.

Table 2.2 summaries different approaches applied for mode detection. According to the detection accuracy of these methods used currently, most of the methods report that the accuracy of mode detection is over 90%. However, overall, none of the complex methods appear to have achieved a higher accuracy than the simple rule-based procedures.

Table 2.2 Summary of Different Approaches for Mode Detection

Author/s	Method	Attributes	Accuracy	Ground truth
Stopher et al. (2008b)	Rule-based algorithm	Speed, GIS, car/bike ownership	95%	Prompted recall survey
Schüssler and Axhausen (2009)	Fuzzy-logic system	Speed, acceleration	n/a	n/a
Biljecki (2010)	Fuzzy expert system	Speed, proximity to the nearest networks	91.6%	Prompted recall survey
Gonzalez et al. (2010)	Neural networks	Speed, acceleration, data quality, travel distance, average dwell time.	90%	User inputted in the mobile phones
Tsui (2005)	Fuzzy system plus an existing neural networks	Speed, acceleration, data quality	94%	Travel diaries
Feng and Timmermans (2012)	Bayesian Belief Networks	Speed, GIS, car/bike ownership, data quality	96%	Travel diaries
Troped et al. (2008)	Discriminant Function Analysis	Speed, accelerometer counts and steps	90%	n/a
Reddy et al. (2010)	Decision tree and discrete Hidden Markov Model	Speed, acceleration	93.6%	Experiment (i.e., mode known)

2.3.3 Trip Purpose Imputation

The next stage in processing GPS data is trip purpose imputation. There are only a few papers that have looked into the area of trip purpose imputation. The traditional process of trip purpose imputation is based on either land-use information (Wolf et al., 2001; Wolf et al., 2004) or a combination of land use and personal information (e.g., home address, possession of vehicles) (Stopher et al., 2008b; Bohte and Maat, 2009).

Wolf et al. (2001) suggested that GIS land use data can be used to detect trip purpose. Based on a vehicle-only survey, they identified 10 categories, i.e., return home, shop, go to work, go to school, pickup/drop-off, change mode, social/recreation, personal business, eat, and unknown. Based on the addresses of different locations, they provided three possible purposes for each location. The previous purpose and arrive time were used to further identify the exact purpose from those three possible purposes. According to a CATI based recall survey, although they only reported 10 wrong purposes (out of a total of 151 trips), 39 trips (26%) are unknown trips and they failed to detect 10 pickup/drop-off trips due to problems of trip identification.

Stopher et al. (2008b) introduced personal information into the purpose imputation to improve the accuracy of the detection, especially for return home trips and work trips. Respondents provided the addresses of home, workplace or school, and the address of the two most frequently used grocery stores. Based on these types of data, they detected purpose correctly over 60% of the time determined by a web-based prompted recall survey.

Bohte and Maat (2009) also applied a rule-based system to detect trip purpose, mainly based on the GIS land-use data and the addresses of home and work place. They suggested that for a non-home or non-work location, if a trip ends within a radius of 50 metres from that location, it can be regarded as a destination. For a home or work location, the threshold is changed to 100 metres. Because home and work addresses are known and frequently visited, a wider radius still would be reliable. The accuracy of their trip purpose detection is 43%. They also used a web-based prompted recall survey to test the accuracy of their detection method.

Except for the influences from TI/SI, the main challenge for these methods is to classify purposes in mixed-use locations such as shopping centres. Bricka et al. (2012) also found that processing algorithms using primary working place only to determine a work trip may under-report work trips. A new perspective of trip purpose imputation is that tour-based trip purpose sequences can be used to correct the initial results. According to previous findings (O'Fallon and Sullivan, 2004; Zhang et al., 2010), there are several possible trip purpose sequences for a tour. A simple sequence would be Home-Work-Home, referring to a tour from home to the work place, and then from work to home. This tour-based information can validate the purpose imputation. For example, Zhang et al. (2010) suggested that a complex work, education and shopping tour (e.g., home-work-education-shopping-home) in people's daily travel occurs very rarely, so that any such instances should be re-examined carefully, to see if evidence is strong in suggesting such a tour.

A decision tree is another method used in purpose imputation (Griffin and Huang, 2005). Trip stop length and the time of trip ends are the two attributes to detect purpose. Their work can only detect some "go to work" trips and "go to school" trips. But for most other purposes, stop time and arrive time alone are not sufficient.

McGowen and McNally (2007) adopted two methods to impute trip purpose – discriminant analysis and classification trees. Their final results for both methods are similar, 72% and 74% accuracy. A very detailed GIS map was used in their research, including all the locations for points of interest (POIs). Thus, they reported more accurate results than other research for shopping and social recreational activities. However, for most research, such detailed GIS mapping is difficult to obtain and it would increase the cost of a GPS survey.

Table 2.3 Summary of Different Approaches for Purpose Imputation

Author/s	Method	Attributes	Accuracy	Ground truth
Wolf et al. (2001)	Rule-based algorithm	GIS land use data	60.9%	Travel dairies
Stopher et al. (2008b)	Rule-based algorithm	GIS land use data, home and workplace/school addresses, address of the two most frequently used grocery stores	Over 60%	Prompted recall survey
Bohte and Maat (2009)	Rule-based algorithm	GIS land use data, home and workplace/school addresses	43%	Prompted recall survey
Griffin and Huang (2005)	Decision trees	Trip stop length and the time of trip ends	90% (work and education)	n/a
McGowen and McNally (2007)	Discriminant analysis and classification trees	Detailed GIS land use map	72% and 74%	Travel dairies

To sum up, there are only a few methods that have been used in trip purpose imputation, and the results of this research are unconvincing from lack of accuracy. Table 2.3 summarises the different approaches for purpose imputation.

The last issue for both mode and purpose detection is "ground truth". The most popular recent method to obtain ground truth is conducting prompted recall (PR) surveys, in which respondents are assisted to recall their actual travel by receiving GPS-generated maps of where and when they travelled. However, PR results are still far from the "ground truth" due again to self-report errors, similar to those in conventional surveys. Most current research uses PR results or PR combined travel diaries as ground truth to calculate the accuracy of mode and purpose detection, or train learning systems. Therefore, the results and conclusions from those research projects must be considered to be questionable.

2.4 LIFE-LOGGING CAMERAS

Life-logging is a process for people to record automatically their own daily life, including both indoor and outdoor activities and all the journeys they make, using a robotic camera. Compared to a travel diary, life-logging is more like a digital diary. Different from the travel diary, this digital diary does not require people to report and record their activities; instead, a digital device passively records all the activities. There are various types of life-logging used in people's lives. For example, a patient who has heart diseases may carry a medical life-logging device to monitor his/her daily health level.

One class of life-logging is called visual life-logging (Wang and Smeaton, 2013). This process usually is supported by a wearable camera taking photos (e.g., SenseCam and Narratives) or videos (e.g., GoPro). This type of life-logging is similar to "activity diaries", which can be used to record travel information. Because taking videos requires more battery consumption for a continuing daily record and may cause more ethical issues, photos are typically recorded as a product of life logging. Most life-logging cameras take photos at a pre-specified frequency or can be triggered to take a photo by changes of sensors or wearer intervention. A fish-eye lens with a wide angle is used to capture the view from the wearer. One day's activities can therefore be "logged" into thousands of pictures. Like most digital devices, battery life is always a concern for users. Since the purpose of the camera is to capture life, most life-logging cameras currently on the market can last approximately two to three days. The life-logging cameras can be very useful in travel data collection because they can capture visual records for all participants' trips and activities on the survey days.

2.4.1 Applications of Life-logging Cameras

With the use of Web 2.0 (e.g., social networks), one of the motivations of using life-logging cameras is to share the moments in one's life with friends. Life logging is becoming a tool for people to use in their leisure time. People can select and post photos taken by cameras in their special events on their social network sites.

The main application of life-logging cameras currently in scientific fields is memory rehabilitation (Silva et al., 2013). People can recall what happened in their lives by reviewing the photos. Several clinical studies have addressed the topic of autobiographic memory (Hodges et al., 2011; Loveday and Conway, 2011; Doherty et al., 2012), and concluded that life-logging cameras will not only benefit memory-impaired patients, but also patients with mental health problems. The main advantage of reviewing the photos for the patients is that the life-logging photos enable people to recall the locations of the events as well as their feelings and emotions during the events. More health-related studies, such as people's sedentary behaviour (Kerr et al., 2013) and dietary analysis (O'Loughlin et al., 2013), have been undertaken by adopting life-logging cameras as a supplementary tool. In addition to the studies of health, life-logging cameras are also used in social reflection (Fleck and Fitzpatrick, 2009), where professionals can review their previous practice and reflect on what they did and improve their practice in the future.

It should be noted that most of the research using life-logging cameras traditionally was based on self-reported notes. Life-logging cameras can overcome the problems of misreporting or false memory that all self-report methods have. Travel surveys, which are also traditionally based on self-report diaries, potentially can use life-logging cameras to collect data, especially when the latest devices — both dedicated GPS devices and Smartphones — used in travel surveys have signal problems. Kelly et al. (2011) investigated active and sedentary travel behaviour by using life-logging cameras. Although their work was initially focused on public health, it shows a potential that these state-of-the-art cameras can help to collect travel information that travel diaries usually report.

The photos captured by life-logging cameras are time-stamped, which could provide the start time and end time for all the activities and trips if trip ends can be detected. Whilst the information of travel modes, trip purposes and vehicle occupancy are the most difficult to obtain in GPS surveys, pictures can visually show the information directly. However, there is no speed information directly recorded by the camera. Therefore, a reasonable suggestion for travel surveys is to use the life-logging camera as a supplementary device, along with GPS devices to collect travel data.

Kelly (2013) used the SenseCam to validate travel diaries. He found SenseCam can capture a substantial number of journeys of less than 3 minutes duration that are thought to be difficult to measure by self-report surveys. He also reported that SenseCam also missed 14% of trips due to respondents failing to wear the devices.

2.5 RESEARCH GAPS FOR GPS SURVEYS

As mentioned above, travel data are critical for transport planning, particularly for travel demand models. Traditional methods (i.e., self-reported interviews) lack accuracy and reliability for recording travel information, which becomes a rationale for using new technology (e.g., GPS, Smartphone, life-logging cameras, etc.) to collect travel data. In the past decade, GPS surveys have been applied increasingly for travel data collection. To obtain more accurate travel data, a number of methods of processing GPS data have been developed during the past decade. The previous section systematically reviewed the approaches to identifying trip ends, detecting travel modes, and inferring trip purposes. Although researchers try to use different methods to obtain accurate results, there are several research gaps in all the steps of GPS data processing.

For the TI/SI processing, it is usually undertaken before mode and purpose detection. Therefore, the accuracy of mode and purpose detection is likely to be highly influenced by the accuracy of trip identification. The errors caused by this step also reduce the accuracy of mode and purpose detection. Furthermore, signal noise and signal loss are still challenging the quality of GPS data. For travel mode and purpose detection, deterministic methods are struggling with the ambiguity of similar modes, such as bicycle and bus. Probabilistic methods are also subject to either long training procedures or a lack of required "ground truth" data. Also, all the methods focus on a single trip (segment) to determine its mode. Yet little has been done on the analysis of a tour-based *mode chain* for people's travel. In the process of purpose imputation, a single point is usually used to represent a place, which would be a problem for the case where the area of that place is large (e.g., airport, university, shopping centre with parking, etc.). Instead, a polygon could be used to represent a place (this study does not address this issue due to time limitation). Also, tour-based information could help refine trip purposes.

Recently, researchers have tried to use different data mining methods, which have been used in different areas, for GPS data processing, especially for mode detection. This is a questionable direction because different methods have pros and cons for different research projects. It is difficult to compare these methods to conclude which one is superior to the other. Since there have been a great number of methods being used in this area, it is definitely worthwhile putting efforts into the improvement of current methods rather than trying different data mining methods. Another potential direction for travel data collection in the future is to use latest technology, which can deal with the current problems of GPS surveys. Bolbol et al., (2010) have proposed Geoweb 2.0, crowd sourcing and user generated content as a possible way to collect data, and enable travellers to upload their trips directly into the web to see them. As discussed in Section 2.4, using passive digital cameras is also a new approach to collect travel data. Travel information, especially for mode and purpose, can be shown visually by images.

Although GPS surveys may still have some issues currently, it is admitted that GPS devices can record more accurate travel information than self-reported diaries, and GPS surveys have become more reliable and cheaper nowadays for data collection, although they are still more expensive in some developed countries (e.g., the US) than travel diaries. With the development of new technology, more new devices could be introduced in travel data collection, along with GPS units, to collect more accurate data.

Based on the gaps mentioned above, this thesis explores two directions (i.e., improve the current processing method and use new technology) to fill the gaps and then produce more accurate data of better quality.

2.6 SUMMARY

In this Chapter, the history of travel surveys was reviewed, followed by a systematic review and comparison between different GPS data processing methods. Research gaps were also discussed. The key points of this chapter are:

- Travel surveys started in the 1950s. The methods of travel surveys include face-to-face interviews, mail survey, CAPI, CATI, CASI, GPS/Smartphone survey, etc.
- GPS technology can directly record location and time of the travel, but trip ends, travel modes, and trip purpose need to be detected by data processing methods.
- The typical procedure in GPS data processing includes three steps: trip identification, mode detection and purpose imputation. Two common methods to process GPS data are deterministic methods (e.g., rule-based algorithm) and probabilistic methods (e.g., machine learning).
- The main gaps in the current processing methods are:
    - The mode detection result is highly dependent on the result of trip identification, which reduces the mode detection accuracy.

- A number of critical rules used in trip identification are arbitrary, which affects the result of identification of trip ends.
- Most GPS studies suffer from signal noise and signal loss.
- There is little research that has addressed the issue of "ground truth", which is important in data processing and validation.
- The purpose imputation result is relatively poor compared to mode detection.

In the next Chapter, the methods used in this study are introduced to address the research gaps mentioned above.

3 METHODOLOGY

In this chapter, the methodology applied in this study is discussed. The chapter starts with research goals and hypotheses in Section 3.1. Section 3.2 introduces how the data were collected for this research. In Section 3.3, a general issue of GPS data processing (i.e., pursuing "ground truth" for validating and assessing the work of GPS data processing) is discussed before the introduction of data processing. A new procedure of data processing is proposed in Section 3.4, which suggests that trip identification and mode detection should be combined as one step. The improvement of trip purpose imputation is introduced in Section 3.5. In Section 3.6, the whole framework of the new approach is demonstrated, followed by a summary of the whole chapter.

3.1 RESEARCH GOALS AND HYPOTHESES

According to the introduction of research gaps in Chapter 2, there are several research goals that are pursued in this thesis (See Table 3.1). In order to achieve these objectives, seven hypotheses are listed for the steps of the new procedure.

Hypothesis I

H1: The threshold of dwell time for an activity is less than 120 seconds.

H0: The threshold of dwell time for an activity is equal to or greater than 120 seconds.

Hypothesis II

H1: One second time intervals are the longest time interval to obtain reliable data for mode detection.

H0: Longer than one second time interval (e.g., 3 seconds, 5 seconds, 10 seconds, etc.) also can provide reliable data for mode detection.

Hypothesis III

H1: life-logging cameras can help find the ground truth.

H0: life-logging cameras cannot help find the ground truth.

Hypothesis IV

H1: 15 successive one-second data points are enough for detecting mode changes

H0: 15 successive one-second data points are not enough or too much for detecting mode changes

Hypothesis V

H1: Combining trip identification and mode detection can increase the accuracy of total detection for travel survey data.

H0: Combining trip identification and mode detection cannot increase the accuracy of total detection for travel survey data.

Hypothesis VI

H1: Automating image processing can be used for mode detection.

H0: Mode cannot be automatically detected from images.

Hypothesis VI

H1: Tour-based information can increase the accuracy of purpose detection.

H0: Tour-based information cannot increase the accuracy of purpose detection.

Hypothesis VII

H1: Additional data (i.e., activity duration, the time when the activity occurs, and the frequency of activity) can improve the accuracy of purpose detection.

H0: Additional data (i.e., activity duration, the time when the activity occurs, and the frequency of activity) cannot improve the accuracy of purpose detection.

Table 3.1 Research gaps and goals

Issues/Gaps	Goals
Mode detection result is highly dependent on the result of trip identification.	Reduce the dependency of mode detection on the trip identification result
A number of critical rules used in trip identification are arbitrary.	Replace the arbitrary rules which are currently used in TI/SI processing
Most GPS studies suffer from signal noise and signal loss.	Reduce the errors caused by GPS signal noise and signal loss
There is little research that has addressed the issue of "ground truth", which is important in data processing and validation.	Investigate a way to pursue "ground truth"
There are limited ways to cope with missing GPS data and to pursue ground truth.	Process data from new technologies other than GPS
The purpose imputation result is relatively poor compared to mode detection.	Introduce tour-based information and other useful travel information for both mode and purpose detection

3.2 DATA COLLECTION

Since 2001, the Institute of Logistics and Transport Studies (ITLS) at the University of Sydney has conducted a number of surveys that involved GPS loggers. The data collected from these various surveys were used in this research for testing purposes. Also, two supplementary surveys were conducted in Sydney, Australia, and Oxford, UK.

3.2.1 Surveys

Among the surveys in which ITLS was previously involved, one survey is the main source from which the data used in this study come: a GPS household travel survey in Cincinnati, Ohio, USA.

The Ohio GPS Household Travel Survey was conducted in 2009 and 2010 by using an address-based sample frame, advance letters, and Internet and phone recruiting and forms reporting (Stopher and Wargelin, 2010). Every respondent in the household over 12 years old was asked to carry the GPS logger for three days when they travelled. A subsample of follow-up prompted recall surveys was conducted to allow respondents to review their GPS travel information from maps for verification. A total of 60,900 trips were collected from 2,059 households in this survey.

With the development of technology and the use of social networks (e.g., Facebook and Instagram), visual images are increasingly applied in people's daily lives. This provides a huge opportunity for travel data collection. To improve data quality and pursue ground truth, two supplementary surveys were conducted in 2012. The British Heart Foundation Health Promotion Research Group, University of Oxford provided the author an opportunity to undertake a collaborative work with them as a visitor in Oxford for two weeks in July 2012. Twelve volunteers were recruited in Oxford, and they were asked to carry both a GPS device and a SenseCam camera, which is a passive digital camera, for three days. The volunteers were mainly university staff and their families. All the participants were over 18 years old. A similar survey was conducted later in Sydney after the collaborative work in the UK, in which seven volunteers were recruited and asked to take one GPS device and one SenseCam for five days. They were also asked to fill out some forms to provide the addresses of home, workplace or school, the address of the two most frequently used grocery stores, and car and bicycle ownership, identical to what ITLS does in GPS-only surveys. Apart from that, volunteers were required to report the occasions when they forgot to carry either or both devices with them when they were travelling, so that it would be known whether there were some trips that both cameras and GPS devices did not record. There was no other paper-based or web-based recall survey afterwards. In these two surveys, the majority of the respondents were students and university staff (i.e., 11 respondents for the Oxford sample and six respondents for the Sydney sample).

3.2.2 Devices

The devices for collecting data were GPS units provided by the Institute of Transport and Logistics Studies at the University of Sydney, and Microsoft SenseCams, provided by the British Heart Foundation Health Promotion Research Group at the University of Oxford.

The GPS device used in this study is manufactured in Taiwan, and was customised to our specifications. This 50 gram device has a rated sensitivity of -158 dbm, with 16 MB of memory. According to the standard NMEA 0183 output stream, this device can store 800,000 records in the 16 MB of storage. The tracking interval is every second, which permits the devices to record about 170 days of data, given that an individual's daily travel time averages 1 hour and 15 minutes (Stopher et al., 2008).
There are three lights on the device: a green flashing light, a blue flashing light and a red flashing light. The green light indicates that the device is searching for a signal; the blue light indicates that the Bluetooth function is on; once the red light is flashing, a position has been acquired. Battery life is usually critical to GPS devices. This device can last 20-26 hours on one charge. Also, with a vibration sensor, the device can last even longer because it turns off recording and satellite searching if there is no vibration for 15 minutes. If the device moves again (i.e., vibration is detected), the device turns on and searches for a signal again. This function not only saves the battery, but also reduces unnecessary data. Voice messages state whether the device is searching for a signal, the signal is found, or the battery is low. The devices are smaller than most

mobile phones (see Figure 3.1), and can be put in participants' pockets or bags.

GPS logger

SenseCam camera

Figure 3.1 GPS Logger and SenseCam Camera

Typically, there are 10-12 variables that can be recorded by GPS devices in transport research. The device used by ITLS can record time, velocity, longitude and latitude, heading, the number of satellites in view, the horizontal dilution of precision (HDOP), the distance travelled from the last recorded point and the altitude (see Figure 3.2). Data can be downloaded in universal coordinated time (UTC) or local time. In this study, UTC was used in the downloading step and converted to local time afterwards. The instantaneous velocity is provided from Doppler measurement, which is much more accurate than using the quotient of travel distance and time. In terms of coordinates, latitude and longitude are expressed in a format of decimal degrees, and positive or negative signs are used to indicate the hemisphere. The number of satellites in view and HDOP indicate the quality of the data. In order to obtain a correct position, at least four satellites are required, because there are four unknowns that need four equations to solve.

Longitude	Latitude	Speed(kilometer)	Course(degrees)	Number Of Satellites	HDOP	Altitude(meters)	DD/MM/YY	HH:MM:SS	Distance(meters)
151.18463	-33.8968	0	90	3	3.95	128	20/8/2012	11:03:36	0
151.184623	-33.8968	0	90	3	3.95	128	20/8/2012	11:03:37	1
151.184616	-33.8967	0	90	3	3.94	128	20/8/2012	11:03:38	1
151.184613	-33.8967	0	90	3	3.94	128	20/8/2012	11:03:39	5
151.184613	-33.8967	0	164	3	3.94	128	20/8/2012	11:03:40	0
151.184636	-33.8968	2	170	3	3.94	128	20/8/2012	11:03:41	9
151.184636	-33.8968	2	166	3	3.94	128	20/8/2012	11:03:42	1
151.184641	-33.8968	0	172	3	3.94	128	20/8/2012	11:03:43	3
151.184641	-33.8968	0	168	3	3.94	128	20/8/2012	11:03:44	0
151.184625	-33.8968	0	168	3	3.94	128	20/8/2012	11:03:45	5
151.184643	-33.8968	2	164	3	3.93	128	20/8/2012	11:03:46	6
151.18464	-33.8969	2	168	3	3.93	128	20/8/2012	11:03:47	3
151.18464	-33.8969	2	172	3	3.93	128	20/8/2012	11:03:48	2
151.18464	-33.8969	2	172	3	3.93	128	20/8/2012	11:03:49	1
151.184636	-33.8969	2	164	3	3.94	128	20/8/2012	11:03:50	0
151.184638	-33.8969	2	170	4	3.2	128	20/8/2012	11:03:51	0
151.184668	-33.8978	2	180	4	3.2	216	20/8/2012	11:03:52	99
151.184631	-33.8979	2	188	4	3.2	222	20/8/2012	11:03:53	5
151.184608	-33.8978	0	188	4	3.2	226	20/8/2012	11:03:54	3
151.184601	-33.8978	0	188	4	31.44	227	20/8/2012	11:03:55	1
151.184598	-33.8978	0	188	4	3.2	227	20/8/2012	11:03:56	0
151.184603	-33.8979	0	188	4	3.19	225	20/8/2012	11:03:57	0
151.1846	-33.8978	0	188	4	31.31	226	20/8/2012	11:03:58	1
151.184596	-33.8978	0	188	4	3.19	226	20/8/2012	11:03:59	0
151.184608	-33.8978	0	188	4	3.19	225	20/8/2012	11:04:00	2

Figure 3.2 Example of Raw Data from GPS Devices

This study also introduced life-logging cameras. The reason that the author decided to use this new device is because it would be impossible to "estimate" travel information for the missing data in a GPS dataset. Using a new device that could record missing parts would be the only way to identify the entire travel details. SenseCam is a passive digital camera (see Figure 3.1) that contains a number of different electronic sensors, which include light-intensity and light-colour sensors, a passive infrared (body heat) detector, a temperature sensor, and a multiple-axis accelerometer. Certain changes in sensor readings can automatically trigger the SenseCam to take a photograph. If nothing changes, it takes time-stamped photos every 30 seconds. Overall, it can capture images approximately every 22 seconds throughout the day and can take approximately 3,000 photos per day (Hodges et al., 2006; Kelly et al., 2011).

In terms of battery, a 980mAh 3.7V lithium-ion rechargeable battery is used for the SenseCam, providing approximately 24 hours of continuous operation. Users can charge the device by plugging it into a PC or USB charger via the USB connection. The full charging time is about three hours.

There is no display on the SenseCam, and a wide-angle lens is used for the camera, which can ensure almost everything in the wearer's view is captured. Participants are asked to wear a camera around their neck, at chest level or higher, in order to capture photos with good quality and view. From those images, travel modes and activities that respondents undertake can be detected (see Figure 3.3).

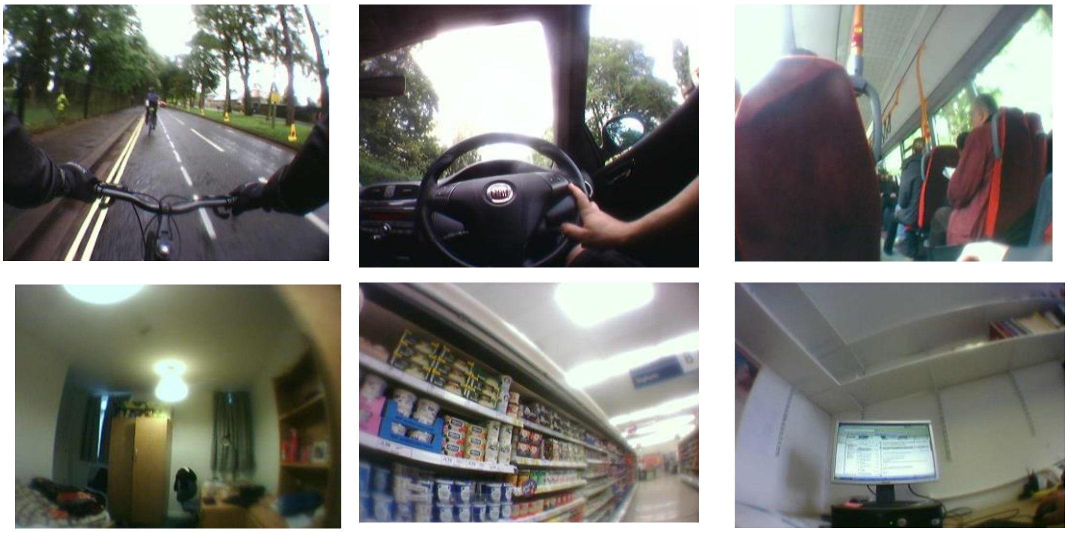


Figure 3.3 Samples of Images Captured by SenseCam

SenseCam's photos are stored as compressed .jpg files on the 1 GB internal memory, and the size of each picture is about 30 KB, which allows the camera to store over 30,000 images. Wearers are not able to download the photos by themselves, so all the photos are downloaded by researchers after the survey. Given that the camera can take 3,000 photos per day, theoretically, a survey can last for up to 10 days.

For privacy concerns, there is a “privacy” button designed for SenseCam. Users can press the button to stop the images being taken. The camera will return to “working mode” after about seven minutes.

3.3 GROUND TRUTH

Generally, the term “ground truth” is related to measurements in cartography, where data collected remotely (e.g., by satellites) are validated by measurements made on the ground. In travel data collection in transport research, ground truth refers to what the traveller really did (e.g., travel time and distance, trip ends, travel modes, trip purposes, etc.). That was the original reason for using a travel diary to ask people to report their travel. However, it has been proved by some of the unquestionable GPS records (e.g., time) that traditional diaries underreport about 20 percent of trips (Stopher and Shen, 2011) that people make and over-report the travel duration. Also, the start and end times of trips reported by respondents are usually incorrect, and people tend to round the time to the nearest 5, 10, 15 or even 30 minutes. Stopher and Shen (2011) conducted an in-depth analysis comparing travel diaries and GPS records. They found that people may report a trip which was made on a different day, or did not even taken place. Although they only focus on trips, reports of mode and purpose from diaries are also questionable. Because of its unreliability, the travel diary should not be used as “ground truth” to report people’s real travel, or validate GPS records.

However, it would be too optimistic to conclude that GPS data represent ground truth, which several very early studies suggest (Wagner et al., 1997; Guensler and Wolf, 1999). The main problems for GPS data are signal loss and signal noise. In addition, respondents have to remember and be willing to carry the GPS device at all times. It has been shown that even a combination of GPS records and self-reported diaries is not ground truth.

The most popular recent method to pursue ground truth is conducting prompted recall (PR) surveys (Bachu et al. 2001; Giaimo et al., 2010; Greaves et al., 2010; Wilhelm et al., 2012), in which respondents are assisted to recall their actual travel by receiving GPS-generated maps of where and when they travelled. Because people have memory issues of reporting what they did in the past, the maps and travel information provided to them from the GPS device that each has taken would help them correctly report or correct their travel to some extent. But PR surveys unfortunately are still far from ground truth. Stopher et al. (2014) investigated the issues of prompted recall surveys. They suggest that self-reported results are still unreliable even if people are provided with detailed travel information from GPS devices. People may misunderstand the definition of a trip, resulting in mistakenly joining/splitting trips, may delete real trips they made, or claim an incorrect mode or purpose according to factual data. For this reason, similar to the diaries, prompted recall surveys cannot provide ground truth to validate GPS results.

It has been increasingly important to obtain ground truth in GPS surveys, because all the methods need to be tested for their accuracy of processing data, and the ground truth is necessary for calculating accuracy. Also, a number of methods used in data processing require training a learning system in which ground truth data are critical.

A recent technological development is that of digital image capture. As introduced in Section 3.1.2, the Microsoft SenseCam has been utilised most in public health research for observation and recording of an individual's health behaviours. This new technology also provides an opportunity for transport researchers to capture ground truth about people's travel. Because there is no signal loss issue on SenseCam and it can take a photo about every 20-30 seconds on average, ground truth can be found by the camera if the camera is working properly when people are travelling during the day. However, this first generation of life-logging camera has a limitation of use, which is that the camera cannot capture clear photos in the dark. According to my study, fortunately, there is only a small proportion of the trips that suffer from this issue.

As a proof of concept test, an investigation was undertaken to see if SenseCam can help pursue ground truth. In order to compare the results from GPS and SenseCam, the data need to be processed.

The G-TO-MAP software (Stopher et al., 2008) was used for GPS data processing to identify the trips, travel modes for each trip, and trip purposes. G-TO-MAP is a rule-based software developed by the Institute of Transport and Logistics Studies (ITLS) at the University of Sydney. In addition to automating data processing, a manual map-editing process was also included, which is undertaken at ITLS about two-thirds of the way through the processing of the GPS data into trips (trip identification). The reason for using map-editing is even with the rules suggested by Stopher et al. (2008) to delete some invalid data, some spurious trips may still remain in the processed data due to signal noise. Some trips may also not be split by the automated process and need to be split by map-editing due to a short dwell time (the threshold of dwell time to identify a stop in G-TO-MAP is 120 seconds). Therefore, deleting spurious trips, adding missing trips, and splitting trips are the main actions in map editing. Deleting a spurious trip takes about 30 seconds, while adding a missing trip takes about 2 minutes. G-TO-MAP can achieve 95%, 90% and over 60% accuracy respectively for identifying trip ends, modes and purposes according to our previous projects, which included prompted recall surveys after the main surveys. The accuracy is based on the results of prompted recall surveys. G-TO-MAP requires GIS maps to detect modes; unfortunately, the GIS layer for bus routes in Oxford was unavailable, so bus trips could not be identified by the application for the Oxford data.

SenseCam images were initially processed by the SenseCam Browser, the software developed by Doherty et al. (2011). This application groups all the images into each activity and/or trip (i.e., splits the journeys into trips) by a learning system. However, automated image processing is always a big challenge. There were a number of trip ends wrongly identified by the software. With the Browser, researchers can visually check each photo and modify the result of identified trip ends. The SenseCam Browser does not have the capability to automate mode and purpose detection, so mode and purpose results need to be added manually when the researchers check the results of trip ends. Mode and purpose information also need to be manually reviewed and determined by researchers from the images. It may take about 10 to 60 minutes (about twice as long as map editing for GPS data) to complete this manual correction for each respondent-day depending on the number and the level of complexity of images being taken.

After the processing, the following results were detected from both GPS data and SenseCam images:

- Trip start time and end time
- Travel mode for each trip
- Trip purpose for each trip
- Trip and activity duration

Trip start time and end time were used as key attributes to link the results of GPS processing and SenseCam processing. A more detailed explanation of G-TO-MAP can be found in Stopher et al. (2008).

SenseCam may miss some trips or stops because of not working properly or because the lens is accidently covered by respondents. So it can be expected that a GPS device needs to be used as a supplementary device. The results are reported in Section 4. The next challenge is, if the new technology can help to provide ground truth, how to automate the data processing. Also, GPS data processing methods need to be improved.

3.4 Data Processing- Trip Identification and Mode Detection

Traditionally, data processing for GPS records includes three steps, namely trip identification, mode detection and purpose imputation. However, the results of mode and purpose detection are entirely based on the results of trip identification. Hence, the total accuracy of a GPS survey would be the product of the accuracy of each step. According to the definition of a trip, i.e., the movement of people between two geographical locations by only one mode for only one purpose, mode detection could actually help identify a trip, especially for the case of mode change. So mode detection should be taken into account in the process of trip identification.

3.4.1 Time Interval for GPS Data Recording

Before identifying trip ends and modes, one principle rule of GPS surveys needs to be tested. Most GPS surveys record GPS points every second (Stopher et al., 2008; Bohte and Maat, 2009), while there are also several surveys (Feng et al., 2011; Mohammadian et al. 2011) using three seconds or an even longer time as an interval to record the GPS data. According to Mokhtarian and Chen (2004), average daily travel time expenditure for a person is 1.1 hours-1.3 hours, so the number of GPS points for that person is about 4000 per day if the time interval to record GPS data is one second. Thus, there will be about 3 million GPS points for a sample of one hundred persons who travel for a week, which would constitute a large dataset. Therefore, a suitable and efficient method to process the data is essential.

One issue of processing GPS data is the processing time. Although the latest computers have increased their capability, it still needs several days to process millions of data points from trip identification to mode and purpose detection. So reducing the number of data points by increasing the time interval of recording data can reduce the processing time and further reduce the data processing cost. (Note that using a 3-second interval would reduce the size of data sets by two-thirds, and a 5-second interval by 80 percent.) Therefore, it is worthwhile testing and comparing different time intervals to see what influences each option would have on the final processing results. Also, with the increasing use of smartphones in travel data collection, increasing the data-recording interval could improve the performance of other devices (e.g., smartphones) to collect data. For instance, smartphones will have a longer battery life if a longer interval for recording data is applied.

This study first tests four options —1 second, 3 seconds, 5 seconds, and 10 seconds—to show the different impacts of each option. Because the purpose of this test is to see if using a longer time interval can generate similar or even better results of trip identification than the one-second interval option, the existing processing procedure was still used.

The G-TO-MAP software was initially designed for processing one-second GPS data. The data collected in this study, which were recorded every second, were processed by the software first. Manual map editing was undertaken to identify the spurious trips (a sequence of points generated by a stationary GPS device that have been incorrectly identified as a trip) based on GPS-generated maps. Map editing is a manual step that is undertaken at ITLS about two-thirds of the way through the processing of the GPS data into trips (trip identification). At that point, when the records have been split into what are thought to be trips by the software, a map is produced for each person-day of data, with each trip shown in a different colour, and each of the recorded data points comprising a GIS layer. This allows a person to examine the map on a computer and, by moving the cursor onto any point, display the data stream for that point from the GPS recording. Even with deleting some invalid data based on the rules suggested by Stopher et al. (2008), some spurious trips may still be recorded by GPS devices and shown on maps due to signal noise. From the map, those trips, which in fact do not exist, are usually shown as people travelling through buildings without any stops, sometimes along with some missing data after these spurious trips. Figure 3.4 shows an example of a spurious trip, shown in red). An in-depth investigation was undertaken, on a case-by-case basis, to check the trips that were initially identified by G-TO-MAP. G-TO-MAP was also used for mode detection and purpose imputation for different time intervals for recording data. Speed (both maximum and average speed), GIS layers, and car and/or bike ownership are the main inputs for mode detection in G-TO-MAP. Land use information, the addresses of homes and work places/schools, and the addresses of the two most-frequently visited grocery stores are the main inputs for purpose imputation.

Figure 3.4 An Example of a Spurious Trip (Shown in Red)

Generally, if a longer interval can be applied in GPS data recording, it can save a substantial amount of processing time and also save storage space for the GPS data. For testing purposes, the intervals of 3 seconds, 5 seconds, and 10 seconds were tested, by dropping out every 2, every 4, or every 9 data points, respectively. Because the data collected for this research were recorded every second, it could be easily converted to an every 3, 5, or 10 seconds dataset by resampling the data.

It could be expected that with the increase of the time interval and decrease of the GPS records, the number of trips and the number of stops that were identified by the software would be different between each option. Some trade-offs would exist, because using longer time intervals may lose several short distance trips due to insufficient points, but it may also add several low-speed trips because those trips sometimes look like "clouds", which are more likely to be regarded as spurious trips and be deleted by automated processing in a one-second dataset. The reason for the "clouds" is because the position accuracy of the GPS device is around ±2.5 m. In that case, the apparent position appears to move around for low-speed trips. The following are the consequences that changing the interval would lead to, together with the reasons why those consequences would occur. Each consequence is investigated in detail, case by case, in this study.

Consequences of changing the interval of recording data:

- Add a new real trip

These new real trips usually have low speeds, and are mistakenly deleted as spurious trips by the software because the points shown on the map look like clouds. With less points recorded in the dataset, the distances between each point become larger, and some "clouds" would become a curve or a straight line so that the software would identify those as real trips.

- Add a new spurious trip

On the other hand, fewer recorded points in the dataset also could create some spurious trips that the software deleted, because the “clouds” would disappear when the number of points decreases.

- Add a new spurious stop by mistakenly splitting a trip

A larger time interval may risk not recording some essential GPS points that record critical information for whether mode is changed. For example, if a person is travelling on a congested road by car, one-second data will record the speed every second, which would show some higher speed values when the car is moving. However, in the 10-second dataset, the chances are that only low-speed values (due to congestion) are recorded, and some high-speed values (when the car is moving) may not be recorded due to the larger time interval. In this case, it might be regarded as a mode change because the person may travel from a free-flow road to the congested road, and the GPS records would show that the speed/average speed of the records change dramatically from high values to low values. As a result, a “spurious” stop may be mistakenly added.

- Add a new real stop

Because the minimum break time is set as 120 seconds for this test, a stop time of less than 120 seconds would not be detected. Increasing the time interval of recording data could increase the apparent stop time, which would add some real stops that are missed by the 120-second rule (for example, if in 5-second data, the last point recorded before a stop was 5 seconds before the stop and the first point after the stop was recorded 5 seconds after travel resumed, then a 110-second stop would appear to be 120 seconds). Also, there might be some spurious points, which look like part of a trip in one-second data, because there are some continuous movements between those points, but the spurious points are actually caused by a stop. In the dataset that has the longer time interval, there would be fewer points and the pattern of those reduced points would not be like a continuous line, so those spurious points would be deleted, which results in adding a real stop.

- Mistakenly deleting a real trip

Similar to the second result of adding new stops, a real trip could also mistakenly be deleted since a real trip could be regarded as a spurious trip due to fewer points when a longer time interval is applied.

- Correctly delete a spurious trip

The reason is the same as the second result of adding new stops, where it would be a whole spurious trip rather than a part of a trip.

- Failure to split a trip which was correctly split in the base option

There might be insufficient points to identify a mode change when a longer time interval is chosen to record GPS data, especially at the beginning or end of a trip when the travel mode switches between walk and car, for example.

3.4.2 Threshold of Dwell Time

The data collected from GPS devices are raw data, without any information on trip ends. In order to process all of these millions of data points, data need to be segmented. A typical procedure of trip identification is actually to apply a threshold of dwell time to segment the raw data and obtain the trip ends. Although a new procedure for processing the data is suggested, segmentation is still necessary. A more accurate segmentation can improve the final results and also reduce the time of map editing. Current processing typically uses 120 seconds (Stopher et al., 2008; Wolf, 2000) as a rule to split the raw data into segments because the traffic signal cycle should always be less than 120 seconds according to the Highway Capacity Manual (2010) and stops for traffic signals should not be regarded as trip ends. However, this arbitrary rule has a problem to find any stop less than 120 seconds, which some activities, e.g., pick-up/drop off or buy a snack at a convenience store, would usually take. Also, different countries may have different maximum traffic signal cycle times, which suggests that 120 seconds may need to be adjusted even if the signal cycle is used as a key criterion. On the other hand, if the threshold of the minimum break time is reduced, more stops may be identified than are actually correct. This study also tests different options for the minimum break time setting to show which one might be the optimal option.

It is common that researchers use a threshold of dwell time to segment travel data to identify trip ends; therefore, using an arbitrary value could cause great errors in the results. The greatest difficulty in identifying trip ends is to find short stops. A longer threshold of dwell time would generate a great number of segments, which would need to be split manually into two or more trips. The purpose of this test is to reduce the number of trips that should be split but which the software failed to split, because 120 seconds could be too long as a threshold, resulting in failure to identify a stop that is less than 120 seconds. This study tested several shorter options, which are 15, 30, 45, 60, 75, and 90 seconds. By re-running the GPS trip identification procedure with a different threshold of dwell time, six new results can be generated. Comparing with the result that is based on the 120-second rule, the number of increased stops can be counted for each option.

The next step is to examine those added stops to see whether they are real stops or spurious stops, because a threshold of dwell time which is less than 120 seconds may detect more real stops which are not found by the 120-second rule, but it could also create more spurious stops. There are three types of spurious stops: a stop due to traffic (i.e., congested road), a stop at an intersection (e.g., waiting for traffic signals), and a stop at a bus stop/train station for boarding and alighting of other passengers. So the main map-editing task is switched from splitting trips to joining trips. However, according to experience in map editing, the cost of deleting a spurious stop (or joining two trips) is much less than the cost of splitting a trip. After segmentation, the first result (R1) can be obtained for the next step.

3.4.3 Mode Change and Detecting Walking Trips

From R1, raw data are separated into segments. The next step is to identify cases of mode change. Logically, if a person needs to change a mode, walking should be involved. In this study, five modes are identified – car, bus, train, bicycle, and walk. Figure 3.5 shows all the possible changes from mode to mode.

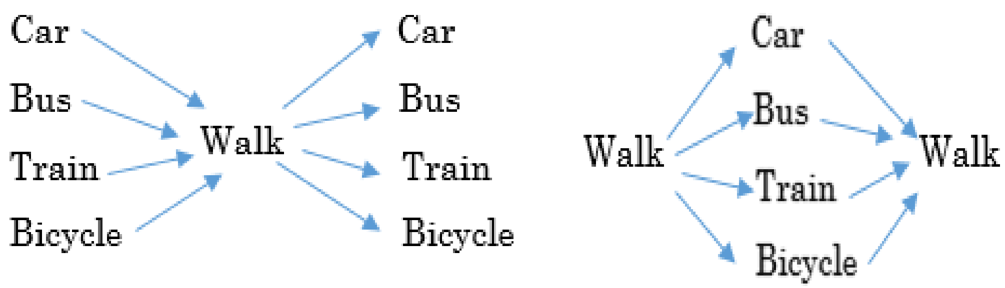


Figure 3.5 Possible Cases of Mode Change

Based on this logic, a walk trip needs to be identified to see if there is any mode change. The rule for identifying a walk trip is applied in the GPS data processing based on the attribute of speed. Different from the normal processing procedure, this step is to check the mode for each data point. Because there are millions of data points, the rules created for each point should be simple, but effective. If the speed of one data point is equal to or less than 6 km/h, "walk" is assigned to that point. If the speed is more than 6 km/h, "other" is assigned. However, people may travel in other modes with a low speed, e.g., travel by car on a congested road. Most existing methods investigate the maximum speed and average speed as attributes, but it would not be useful to identify the mode change by these attributes.

A new way to check if it is a mode change between two points or mistakenly identified mode for one of the points is to create a mode-point-chain. Ideally, the case shown in Figure 3.6 represents a mode change.

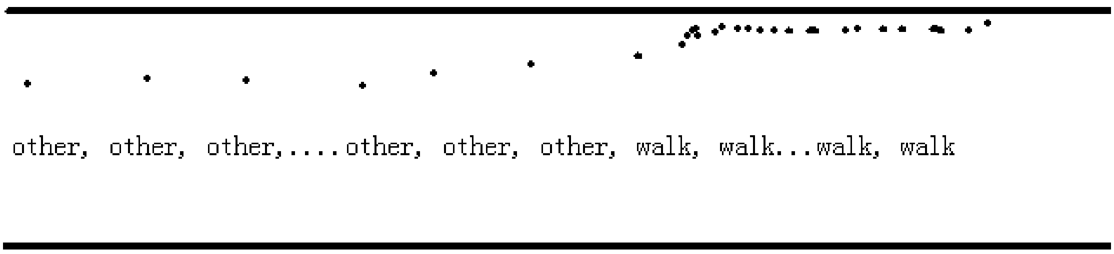


Figure 3.6 An Ideal Case of a Mode-Point-Chain for Mode Change

However, a real case would more likely be similar to that shown in Figure 3.7. In order to fix this issue, and identify the real cases of mode change, some rules need to be created.

Rule 1: If “walk” is assigned to at least 15 seconds of continuous data points, and “other” is assigned to the point before or after the “walk chain”, then it is a mode change. The “walk chain” which is more than 15 seconds is detected as a walk trip.

Rule 2: If “walk” is assigned to no more than 15 seconds of continuous data points, then “walk” is changed to “other”.

Rule 3: If “other” is assigned between walk trips, and there are less than 15 seconds of continuous data points marked as “other”, then “other” is changed to “walk”, and the walk trips need to be joined.

Rule 4: If Rule 2 conflicts with Rule 3, execute Rule 2 first.

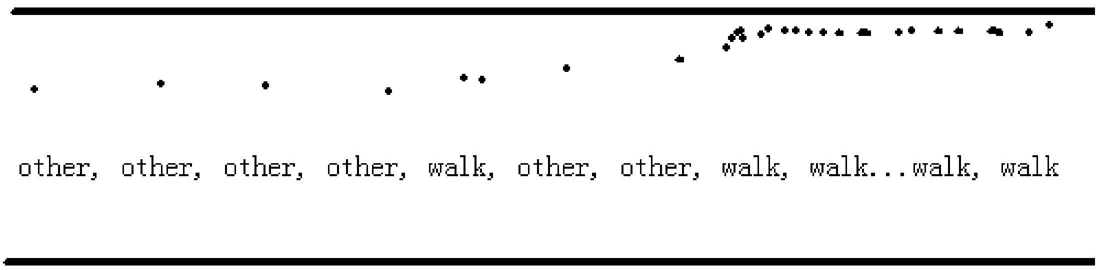


Figure 3.7 A Real Case of Mode-Point-Chain for Mode Change

After the analysis of mode change, all the walk trips can be detected. As discussed in Section 3.2, potentially SenseCam can be used to identify modes. However, walking is relatively difficult to be identified from images because the view from the walker varies. Also, walking can be easily detected by GPS data based on the attribute of speed. Therefore, all walking trips are detected only by GPS data

3.4.4 Detecting Train Trips

The rail system is a special system for processing data. In this study, train refers to heavy rail, which does not share “roads” or tracks with other modes. Train would be difficult to detect if only based on the GPS attributes. The speed of train would be similar to car, and the stop duration in train stations would also be similar to the car’s waiting time for signals. For this reason, the information from a Geographic Information System (GIS) is usually used as a supplementary source to process the data.

In this study, GIS information is obtained from two main sources. The first is OpenStreetMap (OSM). OSM is a project originally created in the UK in 2004. The purpose of this project was to provide free world-wide geographic data. The GIS data of most countries can be downloaded from OSM. Although OSM mainly focuses on transport facilities, it also collects land-use information. The UK GIS layers were downloaded, including the networks of road, train, and rivers. The second source is from the Bureau of Transport Statistics of NSW. A Transport Data Exchange (TDX) program offers students the NSW GIS information for free. Although OSM also provides Australian GIS layers, the layers from TDX are more up-to-date. Similar to OSM, TDX provides all the GIS layers of transport networks in Sydney. Figure 3.8 shows an example of a GIS layer of rail networks.

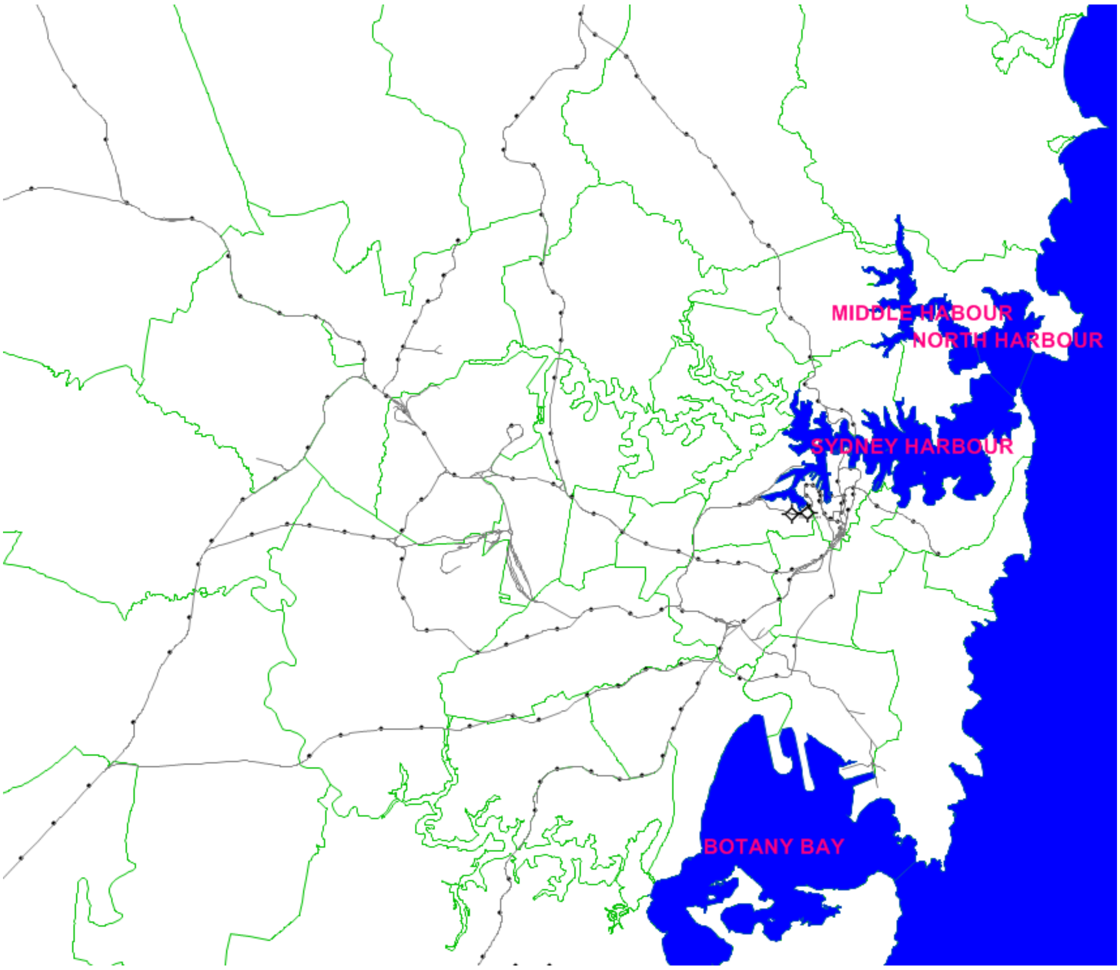


Figure 3.8 GIS Layer of Rail Networks of Sydney

Before identifying if the trip is on a train route, GPS data need to be linked to the GIS map, which is called link matching or map matching. G-TO-MAP uses TransCad® or Maptitude® to complete this task. This step usually takes a long time. Once the map-linking is completed, software can detect if the trip is a train trip. The approach used in this step is to calculate the distance between each GPS record and the train route. As is well known, GPS positions are acquired by solving (at least) four equations. Because the number of satellites acquired is different, GPS positions would have errors from their real locations. Hence, if the distance is less than a certain value, the trip can be regarded as a train trip.

3.4.5 Detecting Car, Bicycle, and Bus Trips

Different from walk and train, bus, car, and bicycle are typically difficult to distinguish by GPS mode detection procedures. They share the same roads, and the speed for each mode is similar especially on congested roads. Therefore, SenseCam images are used to detect these types of trips. Figure 3.9 shows the procedure for detecting modes from GPS data and SenseCam images.

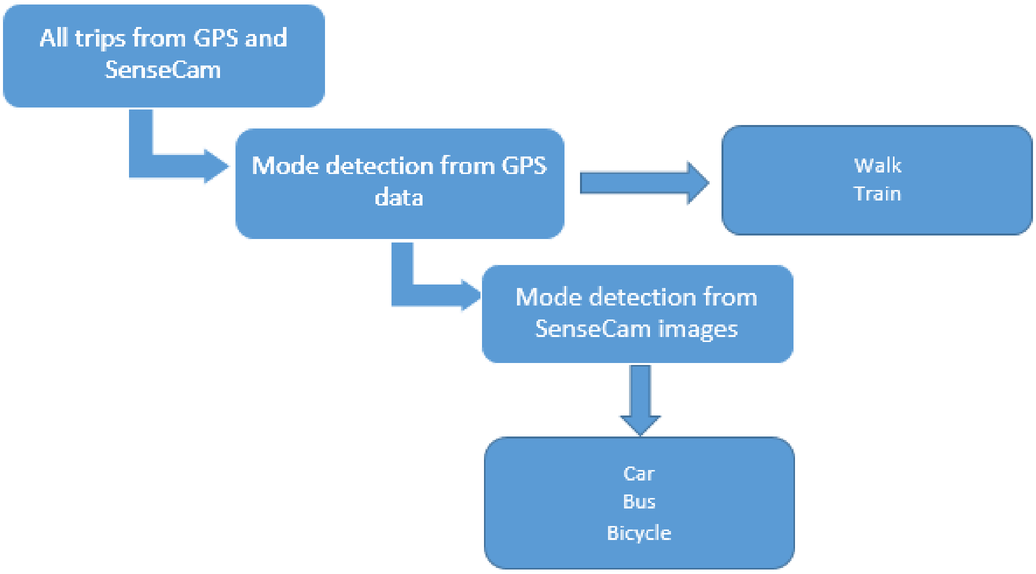


Figure 3.9 A Procedure for Detecting Modes from GPS Data and SenseCam Images

Because walk and train trips have been detected by GPS records, these records can be removed in this step. Also, GPS records can show if respondents are stationary or in a building to undertake an activity, because GPS devices would be in a "sleep mode" for those cases. Hence, the remaining data only shows the movement of people by car, bicycle, and bus. First, images and GPS records need to be linked. Images do not have coordinate information, so GPS records are still important. The connection between GPS records and SenseCam images is time. Both records are time-stamped, so they can be easily linked according to the time, although the time intervals for the two devices to record/capture the data are different. Then the mode detection task depends on the processing of the SenseCam images.

Like most processing work, image processing for SenseCam images starts from a visual check. As introduced in Section 3.2, modes can be visually identified via a SenseCam Browser by reviewers. However, it takes up to one hour to review one person-day of data. Given that household travel surveys usually include thousands of days of data, an automatic approach to process the images is necessary. The main challenge of this step is that cameras have never been adopted for travel data collection. Although image processing has been applied in many other fields, no similar photo has been processed to such a detailed level.

There are two ways to detect modes for each trip. Because the raw data have been segmented by the threshold of dwell time, and images are linked to GPS data points, the easiest way is only to process one image for each segment. This would be very similar to the idea of detecting modes after the trip identification results have been obtained. The problem with this idea is that there might be some errors in trip identification results, so the best way is to process all the images to detect the mode for each linked GPS record and also to see if there is any mistake from trip identification. Because the time interval of capturing photos is about 20-30 seconds, the number of photos is much less than the number of GPS points.

Automating image processing for mode detection has six steps – image input, converting images to greyscale images, edge detection, mode detection, results output, and exit (see figure 3.10). The first three steps are also called pre-processing, which converts the raw images to files with a suitable format for image processing.

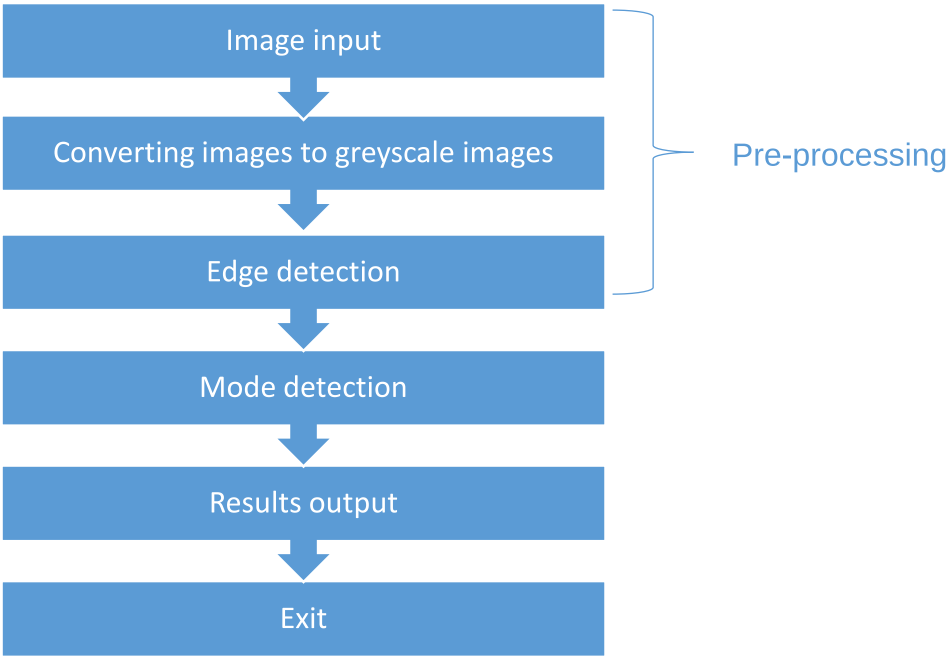


Figure 3.10 Image Processing for Mode Detection

3.4.5.1 Image Pre-processing

The first step is to convert images to greyscale images. The reason for this step is to increase the processing speed on the basis of keeping all the useful information. As introduced in Section 3.1.2, SenseCam images are stored as full colour .jpg files. Based on the purpose of this study, colour is not critical for detecting modes.

Because image processing is to distinguish car, bus, and bicycle trips, finding critical features for each mode is important. From the images for car, bus and bicycle in Figure 3.11, there are a number of features that can be found.

Figure 3.11 Images for Bus, Bicycle and Car

For bus, the features can be seats, people, handrails, views of the road, etc.; for bicycle, the features can be two hands from the cyclist, the bicycle handlebar, roads, traffic, etc.; for car, the features can be drivers hands, the A pillar of the car (the A pillar is the near vertical supports of a car's front windshield), the steering wheel, window reflection, road, traffic, etc. The views from bus passengers are highly variable. It might be easy to find the critical feature for passengers who are seated, but for those who are standing, the features can change for every photo. There is no way to find a single feature for bus passengers. For car driver and bicycle, because the wearer's gestures are relatively stable on a bicycle or in a car, some features are always visible. The bicycle handlebar in the photo is a critical feature for bicycle trips. It can be captured for most cases when people are cycling. Similarly, the A pillar and the steering wheel are the two critical features for car trips when the wearer is a driver.

The data collected in this study for car trips is only from car drivers. Based on this, this study only detects car-driver trips and bicycle trips from images. Because there are five modes in total that need to identified, if car-driver and bicycle trips can be detected, and walk and train trips are detected by GPS data processing, the rest of the trips are bus trips. More discussion about car trips made by car passengers is provided in Section 5.4. Comparing the two critical features for car-driver trips, the steering wheel is easier to capture than the A pillar. Given that all private vehicle trips were made by drivers in this study, the steering wheel is picked as a critical feature for a car trip.

In order to capture the critical features for car (i.e., the steering wheel) and bicycle (i.e., the handlebar), the edges of these features need to be detected. Generally, there are a few edge detection operators (Gonzalez et al., 2003), e.g., Sobel, Roberts, Prewitt, Canny, etc.

The Sobel operator is one of the classic operators used in edge detection. It uses two 3x3 convolution kernels (Figure 3.12) to calculate the horizontal and vertical changes. The two kernels are convolved with the original image (i.e., I(x, y)) to get $G_x(x, y)$ (a horizontal value of a point in an image) and $G_y(x, y)$ (a vertical value of a point in an image). The gradient magnitude can be defined as: G=$\sqrt{G_x^2 + G_y^2}$. The gradient's direction is $\theta = \arctan\frac{G_y}{G_x}$. Similar to the Sobel operator, the Prewitt and Roberts cross operators also use Kernels being convolved with the original images. The masks they use are also shown in Figure 3.12.

$$\begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \qquad \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

3x3 Kernels for the Sobel operator

$$\begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix} \qquad \begin{bmatrix} +1 & +1 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

3x3 Kernels for the Prewitt operator

$$\begin{bmatrix} +1 & 0 \\ 0 & -1 \end{bmatrix} \qquad \begin{bmatrix} 0 & +1 \\ -1 & 0 \end{bmatrix}$$

2x2 Kernels for the Roberts cross operator

Figure 3.12 Masks Used for Different Operators

The Canny detector uses a different way to detect the edge of objects. The first step of Canny detection is to use a Gaussian blur to reduce the noise. The second step is to obtain the strength and direction of the gradients. Then Non-maximum suppression is used to pick up the better “candidate edge”. The last step is hysteresis controlled by two thresholds (i.e., high and low). If the gradient of a pixel is higher than the high threshold, the pixel is a part of an edge. If the gradient is lower than the low threshold, the pixel is excluded as a part of an edge. The values between the high and low thresholds would not be considered as a part of an edge unless they are connected to the pixel whose gradient is higher than the high threshold.

The advantage of classical operators (Sobel, Prewitt, and Roberts) is that they are simple, and processing time would be less than a complex operator. However, they are noise sensitive. The quality of photos from SenseCam differs due to environmental changes (e.g., light, weather, etc.), so photos may have noise. The Canny detector, on the other hand, can perform better in noisy conditions. Therefore, the Canny detector is expected to be a more suitable edge detector.

In the process of edge detection, a circle for a steering wheel and a "T" bar for a bicycle handle bar can be detected. A Hough transform can be used in the next step, because compared with other methods, it is less affected by image noise. Also, the shapes of the critical features for car and bicycle are relatively simple.

3.4.5.2 Hough Transform

A Hough transform was introduced in 1959 (Hough, 1959) and first used to find lines in images a decade later (Duda and Hart, 1972). The goal is to find the location of lines, circles or other structures in images if the parametric equation of those structures is known. Generally, a Hough transform is used for detecting a shape from its boundary points. Points, lines, and curves in image space are associated with some kinds of shapes in Hough space. A line can be described as $r = x\cos\theta + y\sin\theta$, where r is the perpendicular distance from the line to the origin, and θ is the orientation of r with respect to the X-axis. So each point (x, y) on this line will be a sine wave (r, θ) in Hough space. All the waves will intersect at one point in Hough space. This point is associated with the line in image space (see Figure 3.13). Similarly, a circle in image space can be described as $(x-a)^2 + (y-b)^2 = r^2$. In this study, because the radius of a steering wheel is unknown, each point (x, y) on this circle (i.e., the steering wheel) will be a cone (a, b, r) in Hough space. All the cones will intersect at one point in Hough space, representing the circle in image space (see Figure

3.14). If a circle or a "T" bar is detected, a mode of car or bicycle can be determined.

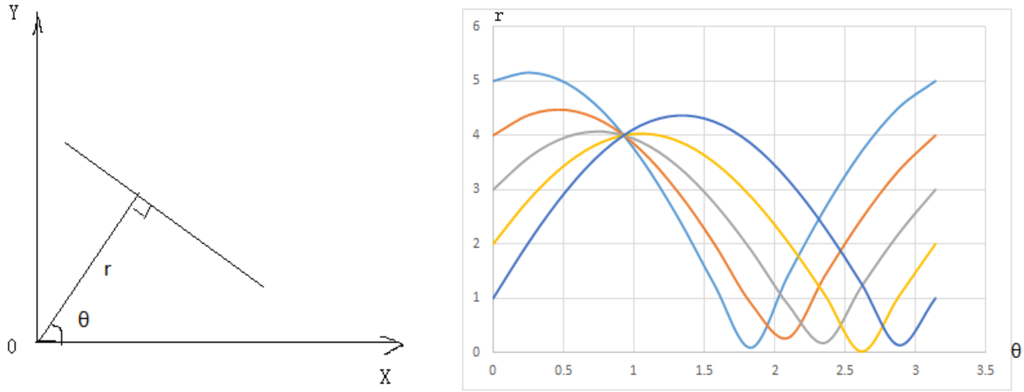


Figure 3.13 A Line in Image Space and Hough Space

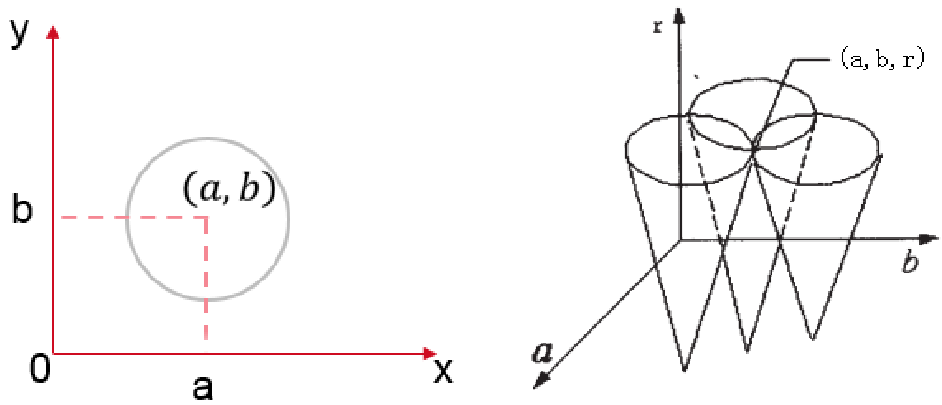


Figure 3.14 A Circle in Image Space and Hough Space

Following the detection results for car trips and bicycle trips, bus trips are also identified. Because the detection is for each photo, a "mode chain" is then created. There might be some cases of mode change that the previous step did not detect. For example, a person might be dropped off at a bus stop, and a bus may be just coming after the person gets out of the car. There is a very short walking time between car and bus, so this case of mode change would not be detected in the previous detection. However, by applying a similar rule to that used in the detection of mode change for GPS records, the "mode chain" can help to find if there are more cases of mode change. Also, some mistakenly-detected modes can be fixed by the "mode chain". After this step, a final result for trip identification and mode detection is generated.

3.5 IMPROVEMENT OF TRIP PURPOSE IMPUTATION

In terms of purpose imputation, images potentially could be processed for purpose imputation, but there are several limitations to such a process, so that automating this work is not included in this research. First, there are few features that can be identified for each activity, which would be a major challenge for automating image processing. Second, for those activities that can be detected relatively easily by images (e.g., work), GPS records can produce more accurate results based on the location where the activities occur. However, since trip and mode results can be identified before purpose imputation, picking one photo for each activity to manually check the purpose would be possible. Before transport research, SenseCam was used in different areas. A visual check is still used to identify what people actually do in an activity. This study actually can reduce a large amount of visual processing time after identifying trips and modes for current research in, for instance, physical activities.

Because automating image processing for purpose imputation is too complicated to accomplish currently, an improved process for GPS data processing is proposed. The idea is to examine the effects of tour-based information and additional activity information on trip purpose imputation from GPS travel data.

Based on the traditional process, some additional information about an activity, i.e., activity duration and the time when the activity occurs, is analysed in this study for purpose detection. The 2009 National Household Travel Survey (NHTS) in the US (U.S. Department of Transportation, Federal Highway Administration, 2009) was used as a basic data source for analysing the distribution of the additional travel information mentioned above and tour information of people's daily travel. A case study of the GPS survey in the Greater Cincinnati region was undertaken (see Section 3.1.1).

Although some research has adopted probabilistic methods to impute purpose from GPS data (Griffin and Huang, 2005; McGowen and McNally, 2007), the approach taken in this research remains a deterministic approach, developing additional rules for classifying purposes. The reason for this stems partly from the fact that early GPS work provided data with much less accuracy than is currently possible to achieve, and therefore has not provided an adequate pool of information that could be used in probabilistic approaches, and partly because a reliable source of 'ground truth' about travel is not yet available (Bohte and Maat, 2009).

3.5.1 Approach and Data Analysis

The NHTS data are used as source data to obtain the basic information that can be applied to the case study (i.e., the Greater Cincinnati region GPS-only survey). The basic travel information includes the distribution of the activity duration, the distribution of the time when the activity occurs, and tour information.

3.5.1.1 Distribution of Activity duration

People undertake different activities normally for different durations. Typically, there are some basic rules for some activities in terms of duration, e.g., working may take four to eight hours per day and education may take three to six hours per day. Since the NHTS data are used and they include residents over the age of five, while the data in the Greater Cincinnati region only included residents over 12, the first step was to exclude children from age five to twelve from the dataset. Also, certain adult proxy reporting data were removed due to lack of accuracy. Greaves (2000) found that people who have their travel information reported by proxy reporting can under-report their travel by 18 percent. This study focuses on the activities of work, education, shopping, being at home and others. Therefore, all the trips in the NHTS are categorised into those groups. In this analysis, in-home activities, which mainly occur during nights, are not counted, because information about these activities could not help examine the effects of activity duration on trip purpose imputation. Figure 3.15 shows the proportion of each activity. The number of "going-to-work" and "returning home" trips are respectively 78,395 and 67,117, accounting for 33.6% of total trips. "Shopping" and "Other" are the most probable activities to occur during the day and education makes up the smallest percentage of the activities.

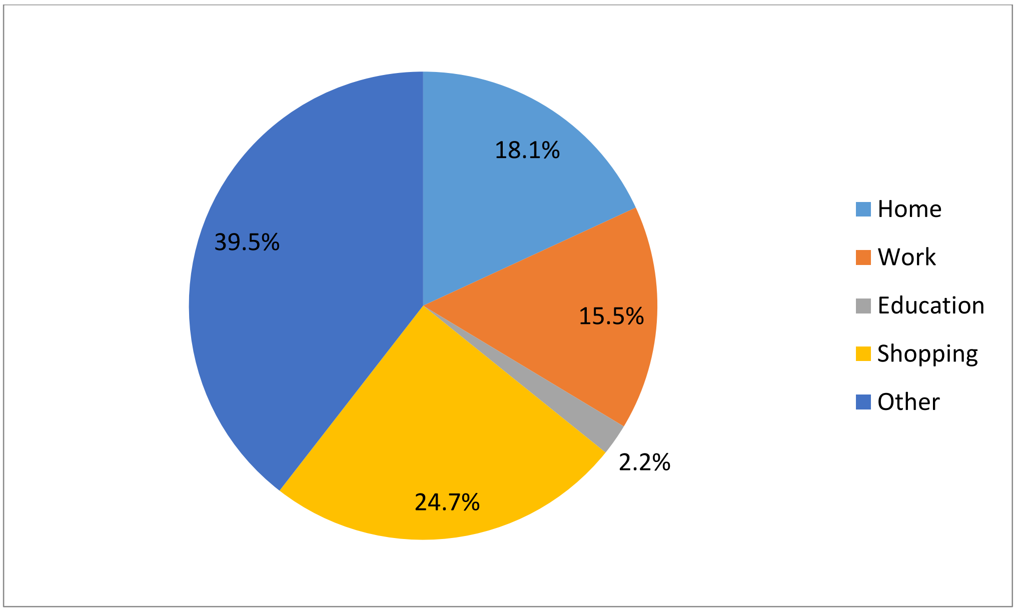


Figure 3.15 Proportion of Each Activity

Figure 3.16 shows the distributions of different activity durations. It illustrates that work and education are more likely to occur when the duration is longer than four hours. Shopping mostly takes less than four hours. Working dominates the activities when duration is longer than eight hours. Therefore, a rule is created to test the effect of activity duration on purpose imputation, i.e., if the duration is longer than four hours and the purpose detected from GPS data is not work or education, this purpose should be suspected as being possibly wrong and the purpose may need to be redefined.

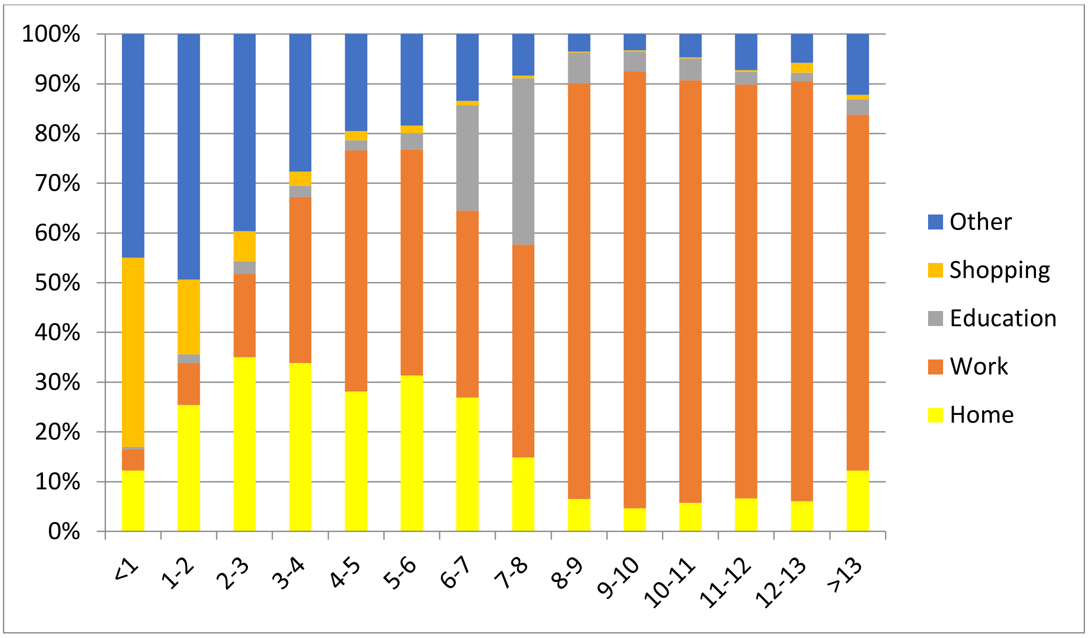


Figure 3.16 Distributions of Different Activity Durations

3.5.1.2 Distribution of the Time When Activities Occur

Similar to the activity duration, there are also some basic rules for the time when an activity occurs. In this section, an activity (i.e., shopping, work, education, home, other) refers to a "travel to" purpose. Working trips (i.e., go to work) are more likely to occur from 8-9 am and finish at 5-6 pm. NHTS data are still used to analyse the basic distribution of the time when activities occur. Different from the analysis of activity duration, the home activities that occur during the night are also counted because the trips for those activities are normally return-home trips, and understanding the time for return-home trips will increase the detection accuracy of those trips. Figure 3.17 shows a 24-hour distribution of the times when activities occur.

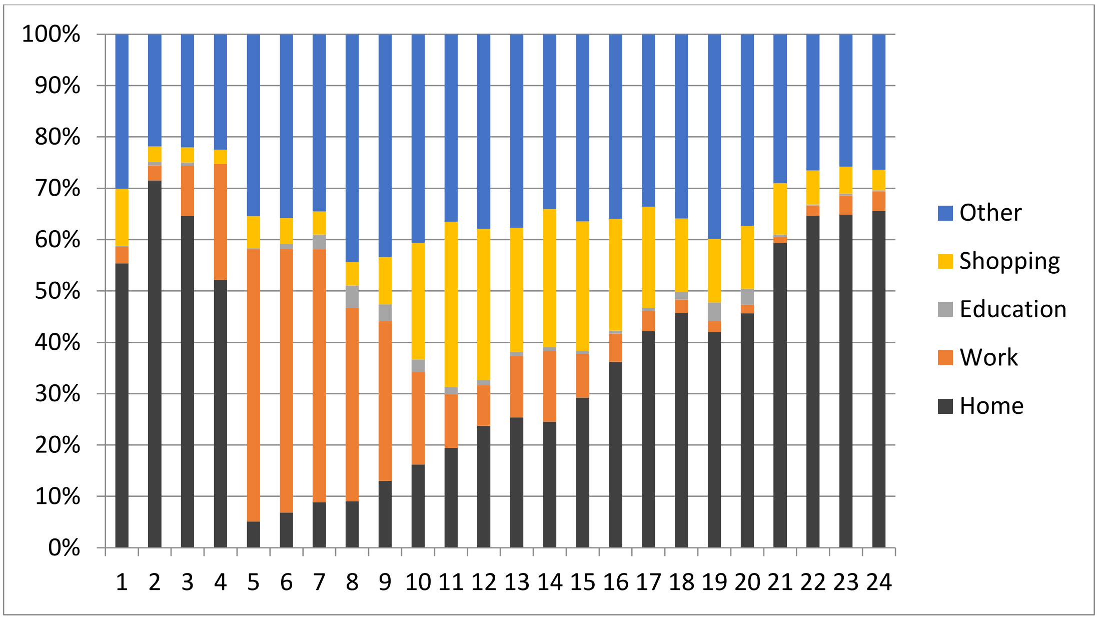


Figure 3.17 24 Hourly Distribution of the Time When Activities Occur

From Figure 3.17, education rarely starts before 5 am or after 8 pm. Working is more likely to start in the morning, which matches the fact that people often go to work in the morning. Return-home trips increase during the daytime. Based on this figure, an activity marked as "education" (i.e., travel to school) from GPS results that occurs before 5 am or after 8 pm may be wrong and may need to be redefined. In addition, combining with the activity duration figure, if duration is longer than 6 hours and the activity occurs before 9 am, the trip for that activity is more likely to be a work or an education trip; and socio-demographic data and addresses of work places and schools could be used to distinguish work and education trips (Stopher et al., 2008).

3.5.1.3 Tour Information Analysis

The next step is to use tour-based trip purpose sequences to correct the results. According to previous findings (Krizek et al., 2003; O'Fallon and Sullivan, 2004; Zhang et al., 2010), there are several possible trip purpose sequences for a tour. A tour is defined as all the travel and activities that occur between a person leaving home and returning home. A simple sequence would be Home-Work-Home, defining a tour from home to the work place and back to home, without any other stops for activities. All the trips are regarded in a tour as a chain, and use reasonable sequences to correct the individual trip purpose. To obtain tour information, NHTS data, excluding children under the age of 13 and adult data reported by proxy, are used. In order to use the entire tour information, missing trips from the self-reported data are manually added. The rules for adding missing trips are:

- If the "purpose from", Pfi, of a trip (not the first trip of a day) does not match the "purpose to", Pti-1, of the previous trip, add a missing trip. The "purpose from" of this added trip, Pfj, is the same as Pti-1; the "purpose to" of this trip, Ptj, is the same as Pfi.

- If the destination of the last trip is not home and the first origin of the next day's trip is home, add a return-home trip.

The same classification as Zhang et al. (2010) suggests was adopted. The count of tours for each tour type is listed in Table 3.2. To be consistent with the analysis in the preceding section, five purposes are included in the tours (i.e., home, work, education, shopping, other). In Table 3.2, the letters "h", "w", "e", "s" and "o" in the "sequence" column respectively stand for home, work, education, shopping, and other. The trip purposes in square brackets must occur in the sequence; and the purposes in bold must occur at least once in the sequence. The purposes in round brackets may not occur or may occur multiple times in the sequence. For example, the sequence h – [**e**/o] – (– **e**/o –) – [**e**/o] – h includes h – e – e – h, h – e – o – h, h – o – e – h, h – e – o – o – h, etc. According to the meaning of the square brackets and purposes in bold, there must be at least three trips in this sequence, and the purpose of "education" must occur. All the sequences must start and end at home. In Chapter 4, the application of this method is introduced to show the improvement of the new rules.

Table 3.2 Tour Type Classifications

Tour type number	Tour Description	Sequence	Count of Tour	%
1	Simple work tour	h-**w**-h	22,209	12.80%
2	Simple education tour	h-**e**-h	4,674	2.69%
3	Simple shopping tour	h-**s**-h	19,969	11.51%
4	Simple other tour	h-**o**-h	54,080	31.17%
5	Complex work tour (including composite and multipart work tours)	h – [**w**/o] – (– **w**/o –) – [**w**/o]–h	13,792	7.95%
6	Complex education tour (including composite and multi-part education tours)	h – [**e**/o] – (– **e**/o –) – [**e**/o] –h	1,552	0.89%
7	Complex shopping tour (including composite and multi-part shopping tours	h – [**s**/o] – (– **s**/o –) – [**s**/o] –h	32,160	18.53%
8	Complex work and education tour	h – [**w**/**e**/o] – (– **w**/**e**/o –) –[**w**/**e**/o] –h	564	0.33%
9	Complex education and shopping tour	h – [**e**/**s**/o] – (– **e**/**s**/o –) –[**e**/**s**/o] –h	1,354	0.78%
10	Complex work and shopping tour	h – [**w**/**s**/o] – (– **w**/**s**/o –) –[**w**/**s**/o] –h	11,579	6.67%
11	Complex work, education, and shopping tour	h – [**w**/**e**/**s**/o] – [**w**/**e**/**s**/o] – (– **w**/**e**/**s**/o –) – [**w**/**e**/**s**/o] –h	207	0.12%
12	Multi-part Other Tour	h – [**o**] – (–/o –) – [**o**]–h	11,382	6.56%

3.6 FRAMEWORK OF THE METHODOLOGY

Since the late 1990s, the methods of GPS data processing have been improved significantly. However, studies on GPS data collection still suffer from signal problems. This study introduces a life-logging camera to assist the data collection. An in-depth investigation of ground truth was conducted by comparing life-logging camera images and GPS records. With the new cameras, more trips and stops are expected to be identified. Therefore, a new procedure to process the GPS data and images was introduced. Figure 3.18 demonstrates the framework of this new procedure.

The first step is to determine the ideal recording interval to minimise the number of data points but still keep the critical travel information. Then the raw GPS data needs to be segmented into segments by using a threshold of dwell time. This study tested different thresholds to find an optimal option. After this step, the first trip identification result can be obtained. However, mode change usually takes a very short time. Logically, walking should be one of the two modes in mode change because people typically cannot directly switch among car, train, bicycle, and bus. There should be a walking trip (even if very short) between two other modes. Therefore, mode change can be identified by detecting walking trips, and seeing if there is a significant change of speed.

GPS data may be the only source at this stage; meanwhile, train trips can be detected from a GIS layer, because it usually does not share a route with other modes. In this study, train refers to the heavy rail in Australia and the UK. If tracks can be detected, train trips are then detected.

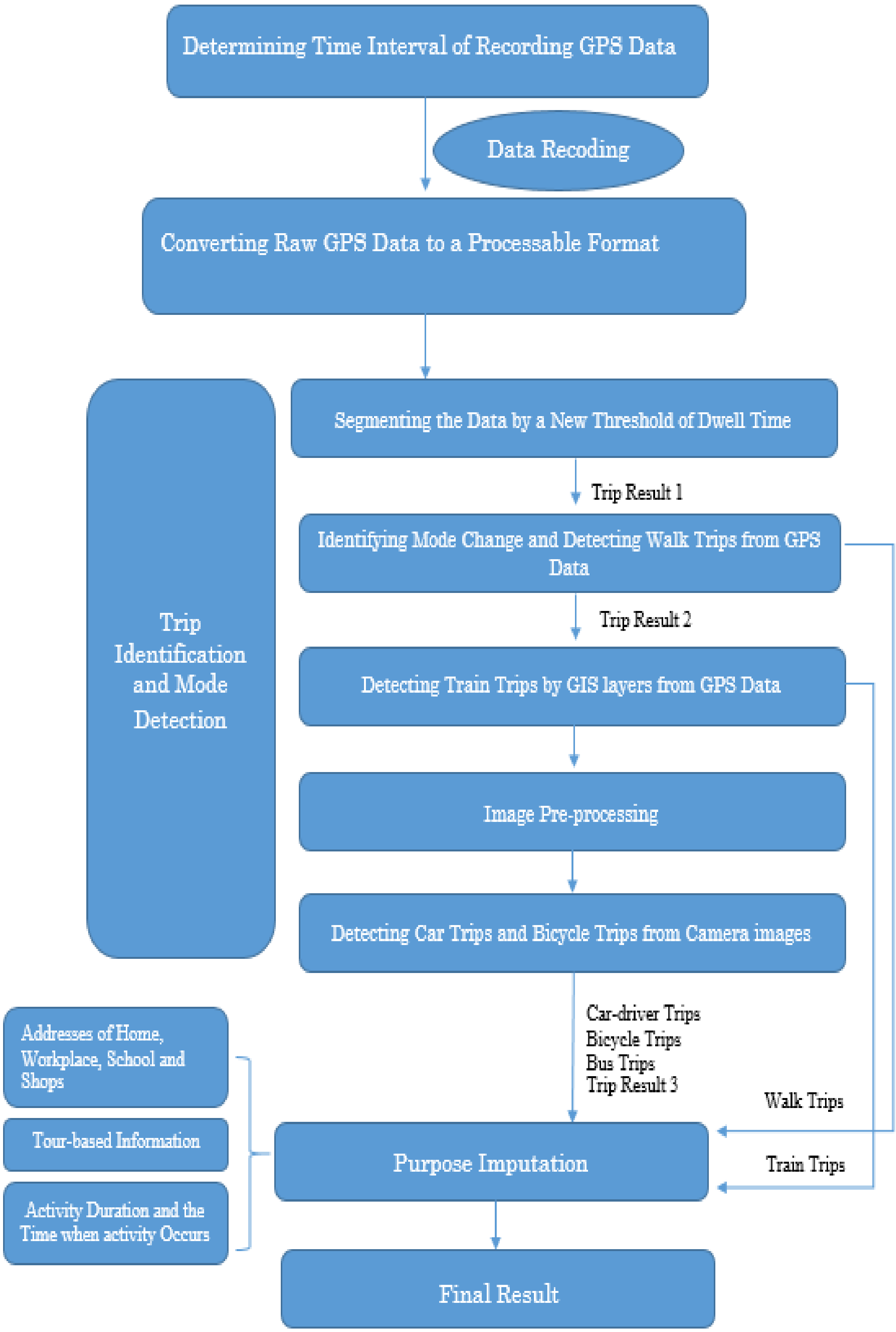


Figure 3.18 Framework of Data Processing

For car-driver and bicycle trips, images from life-logging cameras are applied. The first reason to use images in this step is that bus, car, and bicycle share the same road with a similar speed. It would be difficult to distinguish them only by GPS data. The second reason is that the critical features of car (i.e., the steering wheel) and bicycle (i.e., the handlebar) can be easily captured by life-logging camera photos. The method of edge detection and a Hough transform are applied in image processing to detect car-driver and bicycle trips. Although car-passenger trips were not detected in this study because all the car trips were made by drivers, it could be possible to process images to define car-passenger trips through either the shape of car seats (sitting at back) or the front window (sitting at front) from images. Also, because G-TO-MAP has a process to highlight shared trips within the same household, this also could be used to identify car-passengers in the car. For example, if the car driver is identified, then all the other household members who were sharing a trip were passengers. Once all the other four modes are detected, the remaining trips are bus trips. A mode change detection process also needs to be undertaken in this step. Some cases of mode change may not be detected in the previous step because the walking distance is too short to be identified in the GPS data. After this step, final trip identification and mode detection results are obtained.

Potentially, images can be applied in purpose imputation. However, there are few critical features captured in the images that can determine activities. This study introduced an improved process for trip purpose imputation based on GPS data. Additional travel information, i.e., activity duration and the time when the activity occurs, was proposed to see if the information can be used to improve the accuracy of imputation. Also, tour-based information can be used to correct some mistakes of imputation.

3.7 SUMMARY

In this chapter, hypotheses were proposed and a new approach for processing travel survey data was introduced. Ground truth is critical for validating the travel data processing and also may need to be used for learning processes for artificial intelligence approaches. An analysis of ground truth was suggested in Section 3.3. The methods of testing a threshold of dwell time and an interval of recording GPS data were suggested. A method which combines trip identification and mode detection was discussed in this chapter. This method can overcome a general issue where mode and purpose results are highly dependent on the result of trip identification. Mode change analysis was applied to link the step of trip identification and mode detection, because when mode change is detected, the result of trip identification is changed. Walking trips and train trips were suggested to be identified by GPS data, and car and bicycle trips need to be detected from images. Since life-logging cameras were applied for pursuing ground truth and identifying travel modes, an image processing approach was proposed in this chapter. For trip purpose imputation, additional travel information and tour-based information are proposed to improve the results.

4 ANALYSES AND RESULTS

In this Chapter, some research findings are analysed based on the methodology introduced in Chapter 3. In Section 4.1, an analysis of ground truth is shown to suggest a new way to obtain ground truth. Section 4.2 discusses the result of testing new rules for trip identification. Two case studies are undertaken in Section 4.3 and 4.4 to investigate the new approach for travel information imputation from travel survey data processing. Section 4.5 briefly summaries the whole chapter.

4.1 PURSUING GROUND TRUTH

As discussed in Chapter 3, ground truth is the primary issue that needs to be investigated. Data from life-logging cameras and GPS devices were used for the analysis. The purpose of this analysis is to see if the new technology can obtain ground truth and, therefore, improve the quality of the collected data. Because SenseCam can record all the visual images while a respondent is travelling or undertaking activities, ideally, there would be no missing trips or activities if the camera is working properly and the respondent is wearing it. By visually investigating all the images, it was found that cameras were in proper working condition during most of the survey period; for those periods when cameras were not capturing images or images cannot be identified, GPS devices were working well.

In this analysis, all the data collected in Oxford (UK) was used. By combining GPS and SenseCam data, there are 285 trips recorded in Oxford. Table 4.1 shows the comparison of results between the two devices in terms of trip identification. If both GPS and SenseCam recorded a completed journey (e.g., from place A to B), we marked this trip as a “match”. However, some journeys may include more than one segment (e.g., from place A to C first, then from place C to B), and either the GPS processing software or the SenseCam processing software may fail to detect the stops between segments. We marked these cases as “split by

SenseCam" (where the GPS failed to split the trip, but SenseCam showed a split) or "split by GPS" (for the reverse case). There are 174 trips (61.1%) that match between GPS and SenseCam, among which 113 trips match exactly, 54 trips that should be split were not split in the GPS processing results and 7 trips were not split in the SenseCam processing results.

Table 4.1 Trip Identification Comparison

		Number of Trips	Percent	
Match	Segment match	113	39.6%	61.6%
	Split by SenseCam	54	18.9%	
	Split by GPS	7	2.5%	
GPS map editing		20	7.0%	
Only recorded by SenseCam		66	23.2%	
Only recorded by GPS		25	8.8%	
Total		285	100%	

There are two main reasons for GPS not splitting trips—the trip duration is too short or the stop duration between two trips is too short. In this analysis, the threshold of dwell time to identify a trip is 120 seconds. Due to this rule, less than 2 minutes is defined as "short". According to the results from SenseCam, which split those trips, those cases can be investigated in detail. Moreover, there are 7.0% of trips in Oxford that were not recorded by the GPS devices initially, but were added by a map editing process.

Table 4.2 shows the number of trips that were not split by G-TO-MAP in the GPS results by reason. Because of the rule of identifying stops, the software would have difficulty to split a trip when the dwell time is less than 2 minutes. Also, some trips may be too short and there were insufficient data points so that the software failed to split them. For instance, people may walk from the office to a bicycle parking place or bus stop with a very short distance. In fact, bicycle and bus are actually more frequently used than car in Oxford. It seems that the two reasons have similar impacts (46.3% versus 51.9%), resulting in almost all the cases of failure to split trips.

Table 4.2 Reasons for GPS Failing to Split Trips

Reasons	Number of Trips	Percent
Short duration trips (<2mins)	25	46.3%
Short duration activities (<2mins)	28	51.9%
Unknown	1	1.8%
Total	54	100.0%

The primary reason that SenseCam did not split trips is that SenseCam did not capture the short stop between trips. SenseCam captures images only when there are certain changes in sensors or every 30 seconds if there is no change in sensors. Therefore, for a stop that is less than 30 seconds, SenseCam may miss it. Also, pictures captured in the evening could be too dark to identify a stop.

Returning to Table 4.1, although through the GPS map editing process, 7 percent of trips are fixed, 23.2 percent of trips that were not recorded by the GPS devices could not be fixed by manual map editing. Because SenseCam recorded relevant images during these trips, it can be concluded that these trips are missing from the GPS records. Using the images recorded by SenseCam, the reasons for the GPS to miss data can be examined on a case-by-case basis. This analysis is shown in Table 4.3. Cold starts, short duration trips, and travelling in urban canyons are the three principal causes for the GPS to miss recording data on a trip. Some other reasons, such as people forgetting to carry the device or people switching off the device, cannot be detected by the comparison with images, so those reasons are marked as “unknown”. Cold starts (24.4%) and short duration (33.7%) trips lead to most cases of missing GPS data, whilst 20.9% of trips are missing because of respondents traveling in urban canyons.

Table 4.3 Reasons for Missing GPS Data

Reasons	Number of Trips	Percent
Cold start	21	24.4%
Short duration trips (<2mins)	29	33.7%
Travelling in urban canyons	18	20.9%
Unknown	18	20.9%
Total	86	100.0%

SenseCam also missed some trips (8.8%). Similar to the problem of failing to split trips by SenseCam, inadequate light is also an issue from which all cameras may suffer and is another reason that images cannot be detected. Also, the lens may be accidently covered by participants’ hands or clothes, which will also create difficulties for identification.

Given that there were only a few periods when SenseCam was not working well and GPS devices were recording data for those periods, it is reasonable to conclude that almost all trips and activities were recorded based on the combination of GPS and SenseCam results, although some trips and activities may still be missed during the periods when the SenseCam was not working due to any coincident GPS recording issues. In other words, the combined results of SenseCam and GPS are as near to ground truth as we are currently able to come.

For those trips that are an exact match between SenseCam and GPS, mode detection and trip purpose imputation results also can be compared. Because G-TO-MAP detects public transport modes by GIS layers and the bus route layer is not available in Oxford, 14 bus trips are not detected.

Mode and purpose are visually detected by images without errors. Therefore, the mode results from SenseCam can be used to check the accuracy of mode and purpose detection by GPS data. According to the comparison, 76.1 percent of trips match on mode, and 83.2 percent of trips match on purpose, where work, shopping, education, at home, and other are used for trip purpose. Tables 4.4 and 4.5 show the results of these comparisons.

Table 4.4 Travel Mode Comparison

	Number of Trips (Oxford)	Percent
Match	86	76.1%
Not match	13	11.5%
No bus layer	14	12.4%
Total	113	100.0%

Table 4.5 Trip Purpose Comparison

	Number of Trips (Oxford)	Percent
Match	94	83.2%
Not match	19	16.8%
Total	113	100%

Based on the mode detection results, the missing trips from the GPS records are mainly walk trips (89.2%). Even though the proportion of all walk trips is comparatively high (67.3%) because most volunteers are university staff and their families, and this study focuses on trips/segments rather than journeys, the proportion of missing walk trips is still much higher than other modes, which suggests that GPS may not record walk trips as accurately as other modes. On the other hand, for those studies focusing on vehicle trips, the issue of missing data from the GPS may be of less importance than in studies of pedestrian travel.

Based on this analysis, it is concluded that SenseCam, as a passive digital camera, can help find the ground truth not only for trips but also for travel mode and trip purpose. Also, GPS data are more likely to be missing at the beginning of a trip due to cold starts and for short-duration trips. Those missing trips are more likely to be walking trips, which may not have a large impact on surveys of vehicular travel. This analysis also suggests that trips recorded by GPS devices may be split when a short duration trip occurs at the beginning or at the end of the whole journey or when a short duration activity occurs during the whole journey.

Although life-logging cameras can help obtain ground truth, similar to GPS loggers first being applied in travel data collection, it is questionable as to whether wearing SenseCam would be a new burden for participants. However, because SenseCam is a passive digital camera, it would be relatively easy for participants to carry the devices. Ethics (e.g., privacy) would be another issue for carrying cameras. Kelly et al. (2013) developed an ethical framework for wearing the cameras in related research. They suggested that a good framework would help solve ethical problems. There has not been any research on peoples' willingness to wear this type of camera for travel data collection, which research needs to be done in the future when larger samples are collected.

4.2 New Rules for Trip Identification

4.2.1 Analysis of Comparison between Different GPS Recording Intervals

As discussed in Chapter 3, it is important to investigate the time interval for recording data. An in-depth comparative analysis among four options (one second, three seconds, five seconds and ten seconds) was undertaken. To process the data, 120 seconds was used as the threshold of dwell time to identify a stop. The data collected in Oxford were used for this test.

After the initial GPS trip identification, the total number of trips was 234, based on a base option (i.e., applying the 120-second rule with one-second data) without any manual map editing, including the trips not split by the software and spurious trips. With the simplified map-editing procedure, which only focuses on the investigation of spurious trips, 15.9% of trips were found to be spurious trips. Also, by comparing with ground truth, it was found that the software did not split some trips, and some trips were missed from the GPS processing results. The total trips that respondents actually made (i.e., ground truth) is 285. Table 4.6 shows the result of the base option for both datasets.

Table 4.6 Result of Base Option

<table>
<tr><td>Trip type</td><td>Number of trips</td><td colspan="2">Percent</td></tr>
<tr><td>Real trips</td><td>145</td><td rowspan="2">69.8%</td><td>62.0%</td></tr>
<tr><td>Trips not split</td><td>54</td><td>23.1%</td></tr>
<tr><td>Spurious trips</td><td>35</td><td rowspan="2">n/a</td><td>15.9%</td></tr>
<tr><td>Sub Total</td><td>234</td><td>100.0%</td></tr>
<tr><td>Missing trips</td><td>86</td><td colspan="2">30.2%</td></tr>
<tr><td>Total</td><td>285</td><td colspan="2">100.0%</td></tr>
</table>

4.2.1.1 Comparison of Trip Identification

Three-second, 5-second, and 10-second options were also run through G-TO-MAP. As discussed in Chapter 3, seven consequences (i.e., adding a new real trip, adding a new spurious trip, adding a new spurious stop by mistakenly splitting a trip, adding a new real stop, mistakenly deleting a real trip, correctly deleting a spurious trip, failing to split a trip which was correctly split in the base option) would occur when the interval of recording the data is changed. Table 4.7 shows the results for each option. Due to the increase in the time interval for recording data, some real trips were regarded as spurious trips and mistakenly deleted. In addition, some trips were mistakenly joined. As a result of these two results, 138 real trips recorded in the base option were found for the 3-second option, while 140 and 130 real trips were found for the 5-second and 10-second options, respectively. New real trips were also identified by the longer time interval options. In terms of the 5-second option, it identified 10 new real trips, which is about 5.3% (15 out of 285) of total trips. Also, it correctly split 2 trips. Thus, the total numbers of real trips for the 5-second option is

157 (140+15+2). Similarly, the total number of real trips for the 3-second and the 10-second option are respectively 141 and 142.

Because of this trade-off, compared with 145 trips from the base option, the 3-second and 10-second options have less real trips overall, and the 5-second option identified more real trips. At the same time, some spurious trips were deleted from the 35 spurious trips in the base option; however, new spurious trips were also generated due to an insufficient number of data points. The 5-second option mistakenly regarded the most spurious trips (i.e., 20) as real trips. Although the 3-second option identified the least new real trips (only one), it also generated the least spurious trips. The total numbers of spurious trips for the 3-second, 5-second, and 10-second options are 34, 49, and 41 respectively.

Table 4.7 Comparison of Processing Results between Different Options

Consequence	The Base Option	3-Second Option	5-Second Option	10-Second Option
	Number of trips/stops	Number of trips/stops	Number of trips/stops	Number of trips/stops
Real trips remaining	145	138	140	130
Spurious trips remaining	35	27	29	26
New real trips	N/A	2	15	9
New spurious trips	N/A	7	20	15
New spurious stops	N/A	4	4	5
New real stops (splitting trips)	N/A	1	2	3
Delete real trips	N/A	5	1	2
Delete spurious trips	N/A	8	6	8
Fail to split trips	N/A	2	4	3
Total real trips	145	141	157	142
Total spurious trips	35	34	49	41
Total trips not split	54	57	56	56

N/A= not applicable

Figure 4.1 shows the overall change in the number of real trips and spurious trips. Even though the 5-second option has the most real trips, it is still necessary to be careful to draw a conclusion whether it is the optimal option because of the large number of spurious trips. In this study, the 5-second option identifies more real trips than the other three options overall (12, 16 and 15 more real trips than the base, 3-second, and 10-second options, respectively), and generates more spurious trips (14, 15 and 8 more spurious trips than the other three options, respectively). The cost difference between adding real trips and deleting spurious trips needs to be estimated. Based on the experience of map editing work, manually adding a real trip is much more expensive than deleting a spurious trip. It would take at least 2 minutes to add a new trip; by contrast, removing a spurious trip would only take 30 seconds. The ratios of additional new real trips to additional new spurious trips over the other three options are respectively 12/14, 16/15 and 15/8. All of them are more than the ratio of the cost of adding a real trip to the cost of deleting a spurious trip (i.e., 0.25), which means that the 5-second option can save more time on processing data than any of the other options. For example, the 5-second option in this study saved 17 (12*2-14*0.5) minutes on map editing compared with the base option.

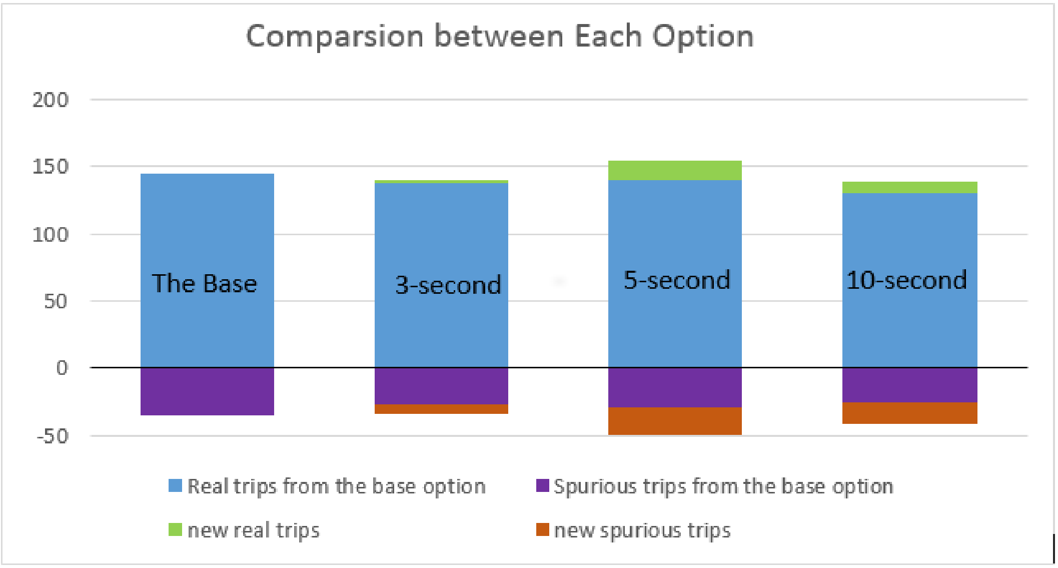


Figure 4.1 Overall Change in Total Number of Real and Spurious Trips for Each Option

In that case, the 5-second option seems to be the best. The benefit from this is that the total number of points would be dramatically reduced (i.e., one fifth of the base option), which will speed up the processing work. However, it is important to note that this result applies only to trip identification.

4.2.1.2 Comparison of mode detection

Applying different time intervals to recorded data will not only change the results of trip identification, but also change the mode and purpose results, because data by these time intervals show travel information at different levels of detail. The results of mode detection by G-TO-MAP were then compared with ground truth for the different options. Table 4.8 shows the accuracy of mode detection for each interval. Because a GIS bus layer for Oxford, which is necessary for G-TO-MAP to detect bus trips, was unfortunately not available for use, the 14 trips that were made by bus in Oxford were not counted in this analysis. The results indicate that the accuracy of mode detection overall is reduced with the increase of the time interval. Table 4.9 shows the details of the detection accuracy for each mode. While the accuracy of detection for bicycle appears to remain unchanged with the increase of the time interval, because G-TO-MAP applies a rule of bicycle ownership as an additional rule to detect cycling trips, the accuracy of detection for other modes decreases. One reason for this decrease is that using a longer time interval to record data could lose some data points that contain important information for mode detection. For instance, the average speed for a car travelling on a congested road may be the same as a bicycle, but the maximum speed for the motorised trip is higher than a cycling trip; however, if a longer time interval is applied, some high speed points could be missing, and a motorised trip may be identified as a cycling trip or bus trip. In addition to that, the less points that are recorded, the more difficult it is for the software to determine if the route of a trip matches a GIS layer of public transport, resulting in failure to detect bus and train.

Table 4.8 Accuracy of Mode Detection for Each Option

	1 second	3 seconds	5 seconds	10 seconds
Match	116	111	119	109
Not match	15	16	24	19
Accuracy	88.5%	87.4%	83.2%	85.2%

Table 4.9 Accuracy of Mode Detection for Each Mode for Each Option

Mode	1 second	3 seconds	5 seconds	10 seconds
walk	98.5% (65/66)	93.4% (57/61)	93.2% (69/74)	94.0% (63/67)
car	100.0% (19/19)	90.0% (18/20)	90.5% (19/21)	89.5% (17/19)
train	100.0% (1/1)	100.0% (1/1)	0.0% (0/1)	0.0% (0/1)
bus	n/a	n/a	n/a	n/a
bicycle	68.9% (31/45)	77.8% (35/45)	66.0% (31/47)	70.7% (29/41)

4.2.1.3 Comparison of purpose imputation

Similar to the comparison of mode detection results, purpose imputation results were also investigated. Tables 4.10 and 4.11 show that the accuracy of purpose imputation is also reduced with the increase of the time interval; however, the range of the decrease is smaller than for mode detection. The main reason for this is the rules used in the imputation. Rule-based purpose imputation is mainly based on the land use information and the addresses of homes, work places, schools, shops, etc. Although the precision of the locations of each stationary point could be reduced due to less points recorded when the longer time intervals apply, the locations would still be close to the actual points, because when a person stops, the GPS points shown on the map would look like a cloud, no matter which time interval is applied. The location of the centres of each cloud, which was used as the point for each stop, for different time intervals would be similar. Therefore, the accuracy of purpose imputation is not decreased substantially as a consequence of the increase of the time interval. However, it does decrease in accuracy, so the more points, the better, meaning that 1-second data is best.

Table 4.10 Accuracy of Purpose Imputation for Each Option

	1 second	3 seconds	5 seconds	10 seconds
Match	125	118	132	117
Not match	20	23	25	25
Accuracy	86.2%	83.7%	84.1%	82.4%

Table 4.11 Accuracy of Purpose Imputation for Each Activity for Each Option

Purpose	Accuracy for Oxford data			
Home	100.0% (45/45)	95.3% (41/43)	95.9% (47/49)	93.0% (40/43)
Work	100.0% (16/16)	100.0% (15/15)	100.0% (16/16)	93.8% (15/16)
Education	75.0% (3/4)	66.7% (2/3)	80.0% (4/5)	60.0% (3/5)
Shopping	100.0% (7/7)	100.0% (7/7)	90.9% (10/11)	88.9% (8/9)
Other	74.0% (54/73)	72.6% (53/73)	72.4% (55/76)	73.9% (51/69)

According to these comparative results, both mode and purpose detection accuracy decreased with the increase of the time interval of recording data. Although the accuracy is still relatively high (i.e., over 80% for both mode and purpose detection), one-second data can provide more detailed information and produce more accurate mode and purpose detection results.

Based on this analysis, it seems that the time interval of recording GPS data can be increased to five seconds for trip identification because with the five seconds interval, the result for trip identification is not worse than the result of one-second data. It can even reduce the cost of map editing. However, for mode and purpose detection, one-second data still can provide the most accurate result, suggesting that a one-second recording interval may still be used for GPS-only data collection, but processing for trip identification with current software could potentially sample the data, using five second intervals between data points.

4.2.2 Results of Comparison between Different Thresholds of Dwell Time

4.2.2.1 Trip Identification Difference between Options

According to the analysis of ground truth, it has been shown that current GPS software has issues to identify a short trip or a stop based on current rules. Therefore, the rule for identifying a stop (i.e., using 120 seconds as the threshold of dwell time) might be changed.

In this study, the data collection from Oxford is used. Six options were run by G-TO-MAP in this study. This analysis focuses on the trips that needed to be split, especially for those stops that are less than 120 seconds. It is expected that the shorter the threshold of dwell time, the more short-duration stops can be identified. According to Table 4.12, 54 trips failed to be split when the 120-second rule was applied. By reducing the threshold of dwell time, more real stops can be identified. According to Table 4.12, if a 15-second rule is applied in the processing, 14 trips can be found, which would include all the stops that are less than 120 seconds. It seems that not many short duration stops were found (25.9%). The reason is that the proportions of walking and cycling trips are higher in Oxford than other major cities in the US or Australia, and there are more short duration trips (less than 2 minutes), where most of those trips occur before or after a case of mode change (e.g., from walk to bicycle, or vice versa). Some trips are often too short which leads to a failure to detect a mode-change case. A 90-second rule only found 1 more short duration stop. Meanwhile, new spurious stops were also added. For the 15-second rule, 51 spurious stops were identified. Given that the total number of real trips is 285, it seems to be too many spurious trips generated. Waiting for signals and stopping at train stations or bus stops are the main reasons for generating spurious stops.

Table 4.12 Comparison of Processing Results between Different Minimum Dwell Time Settings

Consequence	15-second	30-second	45-second	60-second	75-second	90-second	120-second
	Number of trips/stops	Number of trips/stops	Number of trips/stops	Number of trips/stops	Number of trips/stops	Number of trips/stops	Number of trips/stops
New real stops	14	10	10	4	1	1	N/A
New spurious stops (congested	9	8	3	1	1	1	N/A
New spurious stops (waiting for	14	8	6	0	0	0	N/A
New spurious stops (train stations/bus stop)	28	21	15	9	7	3	N/A
Total new spurious stops	51	37	24	10	8	4	N/A
Total trips not	40	44	44	50	53	53	54

N/A= not applicable

Figure 4.2 shows the change in the total number of real and spurious stops for different dwell-time settings. From the graphs, the total number of trips that were not split decreases as the dwell-time setting decreases, while the number of spurious trips increases. There is a cross point between these two curves, which seems to indicate that the optimal threshold of dwell time is between 45 seconds and 60 seconds.

However, the value of this optimal threshold may depend on the specific data, which means that a value between 45 seconds and 60 seconds is not necessarily the best for all data sets. In this study, with the 45-second option, while 6 more new real stops were identified than the 60-second option in total, it generated 14 more spurious stops than the 60-second option. According to the experience of map editing, the cost of deleting a spurious stop is one quarter of the cost of splitting a trip. This means that the 45-second option would be the best option for this study.

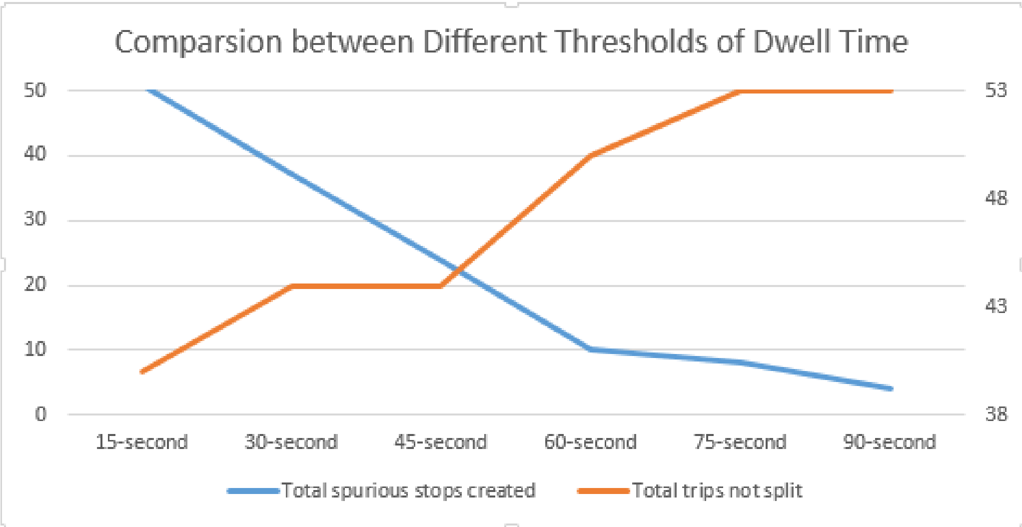


Figure 4.2 Comparison of the Total Number of Real and Spurious Stops between Different Thresholds of Dwell Time

4.2.2.2 Mode and purpose detection for new identified trips/stops

Changing the threshold of dwell time can identify more stops and activities. It is useful to check the modes for those new identified trips. Table 4.13 implies that when people are walking or cycling, they are more likely to undertake an activity of less than 60 seconds duration. On the other hand, once a motorised trip stops, the stop time is more likely to be longer than 60 seconds, although there might be a few pick-up/drop-off stops for car trips.

Table 4.13 Mode Detection Results for New Identified Trips

	15-second	30-second	45-second	60-second	75-second	90-second
Car	3	2	2	2	1	1
Walk	8	6	6	2	0	0
Bicycle	2	1	1	0	0	0
Train	1	1	1	0	0	0

It is also necessary to understand the purpose of those new identified trips. If shorter thresholds of dwell time than 120 seconds can be applied, the purpose of those trips also can be detected. Clearly, pick-up/drop-off and mode change and some short duration shopping activities could be less than 120 seconds. For example, people may go into a store to buy a bus ticket or only to check if something is in stock, which may only take less than one minute. Table 4.14 shows that 21.4% of the new short duration activities identified by the threshold of 15 seconds were shopping. There are still a large proportion of new identified activities marked as “other”.

Table 4.14 Purpose Imputation Results for New Identified Activities

	15-second	30-second	45-second	60-second	75-second	90-second
Shopping	3	3	3	2	0	0
Other	11	7	7	2	1	1

Table 4.15 provides more details for the purpose “other”. G-TO-MAP was supposed to detect all the mode-change stops, but some stops for mode change were too short to be detected. For example, a person may alight from a train, run across the platform and board another train that is just arriving. The whole transfer time would be less than 30 seconds and could be much shorter, and it could be difficult for the software to detect this stop. For the dwell-time option of 15 seconds, pick-up/drop off accounts for one sixth of all the “other” activities, and mode change accounts for 40% of the “other” activities.

Table 4.15 Detailed Trip Purpose for “Other”

	15-second	30-second	45-second	60-second	75-second	90-second
Mode Change	6	3	3	1	0	0
Pick up/drop off	2	2	2	1	0	0
Other	6	5	5	2	1	1

From the analysis of thresholds of dwell time, using the 120-second rule would lose around 20% of the real stops. Although many of those real stops can be fixed by reducing the threshold, more new spurious stops will be created at the same time. Therefore, the stop-time rule might be tightened, but the extent of tightening will depend on the relative costs of splitting trips by map editing, versus deleting spurious stops (i.e., combining trips) by map editing. Considering the trade-offs between the number of new real stops and spurious stops, and between the cost of adding real stops and deleting spurious stops, the 45-second option would be the best option for the dwell time based on the data in this analysis. The mode and purpose detection for new identified trips/stops for each threshold of dwell time suggests that people are more likely to undertake a brief activity (e.g., less than 60 seconds) when they are walking than when they are driving a car. In addition, shopping, mode change, and pick-up or drop-off are the main known purposes of the short duration activities.

4.3 CASE STUDY FOR NEW DATA PROCESSING METHOD FOR TRIP IDENTIFICATION AND MODE DETECTION

The results from Section 4.2 were then used in a case study based on the data collected in Sydney. The new processing method was adopted in this study to process both GPS data and images from life-logging cameras to improve the accuracy of collected travel data.

Because mode and purpose will also be detected, in case some information might be lost if a longer time interval is adopted to collect the data, GPS data were collected every second. Like all the GPS data processing methods, the first step is to convert raw data to a workable format and determine the validity of data by some attributes from the GPS devices, e.g., the number of satellites in view and the horizontal dilution of precision (HDOP). Stopher et al. (2008) explain in detail the rules for cleaning GPS data. The next step is to segment the GPS points into segments. As suggested in Section 4.2, 45 seconds was then used as the threshold of dwell time. Therefore, combining with the rules suggested by Stopher et al. (2008), a trip end can be identified by the following rules:

- The difference in successive latitude and longitude values is less than 6 m; and
- The heading is unchanged or is zero; and
- Speed is zero; and
- The dwell time is equal to or greater than 45 seconds

4.3.1 Trip Segmentation

Initially, there are 312,568 GPS data points for the data collected in Sydney, including the trips from seven volunteers travelling for five to seven survey days. Although the GPS device has a "sleep mode" to stop recording data, the sleep mode is only activated several minutes after a trip is completed. GPS devices still record data for these few minutes. However, the data need to be removed because the trip has ended. Also, some invalid data were removed from the raw data. As a result, from the raw data, the total number of GPS data points was reduced to 102,640 travel points by applying the rules of identifying a stop and the threshold of dwell time. The reasons of this reduction of the number of points are: 1) there were a number of cases that devices should have been in sleep mode but they were not, so the devices continued to record a few hours data where people were actually stationary; 2) data marked as invalid was removed.

These travel points consist of 233 segments identified by G-TO-MAP. In those segments, some are spurious trips, which need to be deleted, and some are actually within one trip, but wrongly split by the rule of the threshold of dwell time. A new map editing process is then adopted. The normal map editing process for G-TO-MAP is to delete spurious trips, add missing trips, and split or join segments by in-depth investigation based on the GIS map or Google map generated by the software. The main challenge is to add missing trips. Logically, the location of an origin should match its previous destination unless it is the first origin of the whole survey. Similarly, the location of a destination should match its next origin unless it is the last destination of the survey. If they do not match, there has to be a missing part between them. It could be a single trip or multiple trips. The information of other trips that the respondent made on the same day or other days can be used to add the information for missing trips. The travel information from other persons in the same household also can be used to assist the process, but the start and end times for those missing trips cannot be estimated. Although respondents were asked to report if they had forgotten to carry the devices for the whole day or just a part of a day, for those cases when people forget to carry their GPS devices, there is no way to add the missing trips by map editing. The other issue is that adding trips by map editing can create new errors due to lack of travel information. According to the analysis of ground truth, life-logging cameras can help to find the trips that GPS devices do not record. Hence, adding missing trips would not be a task for the new map editing process. However, flags were marked at the place of missing trips by comparing the longitude and latitude of origins and their previous destinations and also based on the reports that respondents provided about whether they were carrying the devices. The flags were used to locate the missing trips and help find them by images. Because the threshold of dwell time is decreased to 45 seconds, more trips need to be joined, and the map editing procedure mainly focused on deleting spurious trips and joining segments in this study.

The definition of spurious trips was introduced in Chapter 3. According to the map editing process, there are 28 spurious trips among the segments identified initially. Therefore, the number of real trips is reduced to 205 (233-28). After deleting the spurious trips, all the time-stamped images from life logging cameras were linked to the GPS data.

Because the reasons for wrongly splitting segments are mainly waiting for signals and stopping at train stations and bus stops, map editing focused on those locations to see if there were some segments that needed to be joined (see an example in Figure 4.3).

Figure 4.3 An Example of Joining Segments

4.3.2 Trip Identification and Mode Detection

By deleting spurious trips and joining segments, there are 150 real trips identified. These 150 trips were then marked as R1 for the first result of trip identification. The next step is to identify cases of mode change from R1. Logically, a walk trip should be involved in the cases of mode change. As discussed in Chapter 3, mode change detection was undertaken according to the speed of each GPS point in the segments. The rules for identification were introduced in Chapter 3. Figure 4.4 shows the result of the first trip segmentation and mode change detection.

Within the 150 segments, there are 43 cases of mode change, resulting in 43 more trips. At the same time, all the walking trips were identified by the rules. The total number of walking trips is 100, which makes up 51.8% of the total trips. The proportion of walking trips is relatively high, because this research focuses on the trips rather than journeys, and people usually need a walking trip to link two other trips by different modes. Since the walk trip has been identified, all the GPS points for these walk trips are removed from the dataset for the remainder of mode and trip identification.

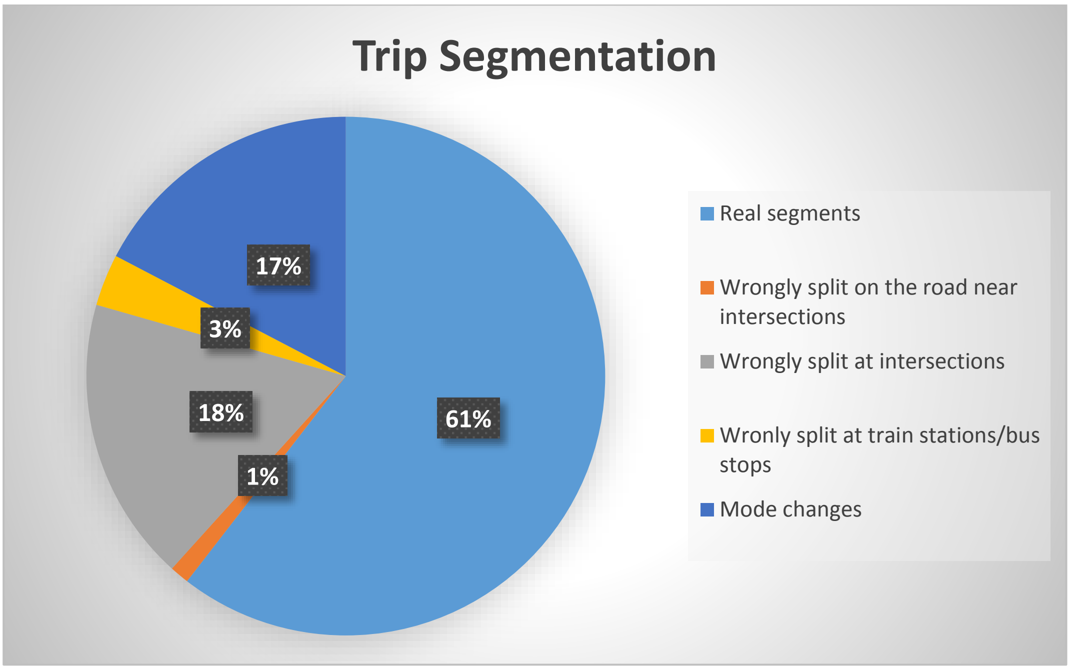


Figure 4.4 Result of the First Trip Segmentation

The next step is to identify train trips. Because train only travels on the track and does not share the track with any other modes, the GIS layer of the train routes is critical to identify a train trip.

By using the GIS layer, a process of link matching is necessary where all the GPS points are linked to a GIS map. In this study, this process was completed by G-TO-MAP. From the segmentation result, there are 93 trips that are not walk trips. Based on the G-TO-MAP process, 18 train trips were identified. All the GPS points for train trips were then removed after this step.

The 75 remaining trips are therefore car, bus and bicycle trips if all the walk trips and train trips were correctly detected. As described in Chapter 3, images from life-logging cameras were applied in the detection process.

Matlab® version 2014a was used in this study to process the images. Matlab® is a software using a high-level language for analysing data, creating models and other applications. It has been used in various areas, especially in information systems, finance, and biology. The language used in Matlab® is simpler than traditional programming languages. Also, because it has a number of built-in functions and toolboxes, it can find a solution much faster than other software based on traditional programing languages. The Image Processing Toolbox is one of the powerful toolboxes in Matlab®. People can use the toolbox to develop their own functions to display and analyse images.

Pre-processing was undertaken before mode detection of the images. After inputting all the images for car trips, bus trips and bicycle trips, all images were converted to greyscale format. Figure 4.5 shows the greyscale images for driving a car and riding a bicycle. The main information in the images was still kept in greyscale images.

Figure 4.5 Greyscale Images for Driving a Car and Cycling

Next, all the greyscale images needed to be converted again to binary images, also known as black-and-white images, for edge detection. There are several operators widely used in edge detection. The critical factor that affects the performance of each operator is the threshold. Generally, the more stringent the threshold chosen, the more detailed the characteristics of the edge that can be detected. Figure 4.6 shows the performance using the Sobel operator with different thresholds.

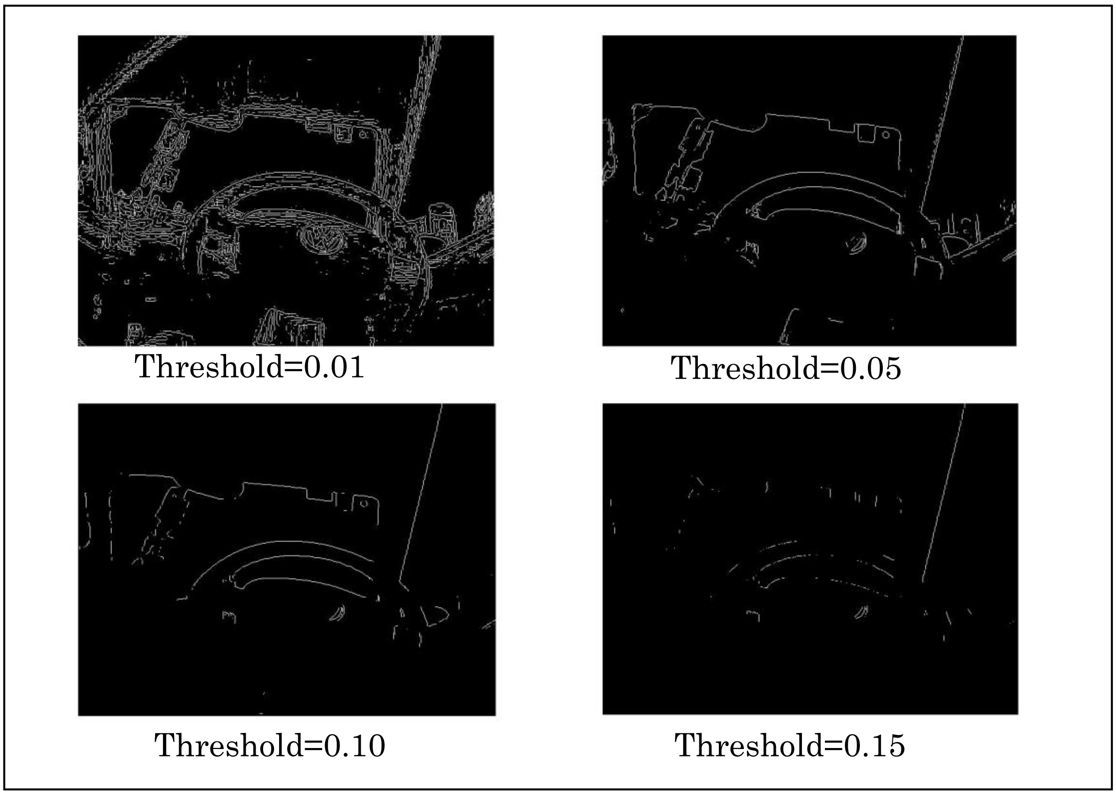


Figure 4.6 Performance of the Sobel Operator with Different Thresholds

Also different operators perform differently in different contexts. In this study, because all the photos were captured by life-logging cameras, there is significant noise in each photo. Figure 4.7 demonstrates the performance of different operators. For the comparison among operators, different thresholds were chosen for different operators in order to reach the best performance for each operator. The ideal result of edge detection is to include all the important and useful information from the images, and also not include too detailed but useless information and noise. Apparently, even with a higher threshold, the Canny detector still performed better than the other three operators. The make of the car (i.e., Volkswagen in this case) was successfully detected by the Canny detector, and the edge was much clearer with less noise. As a result, the Canny detector was chosen for edge detection in this study.

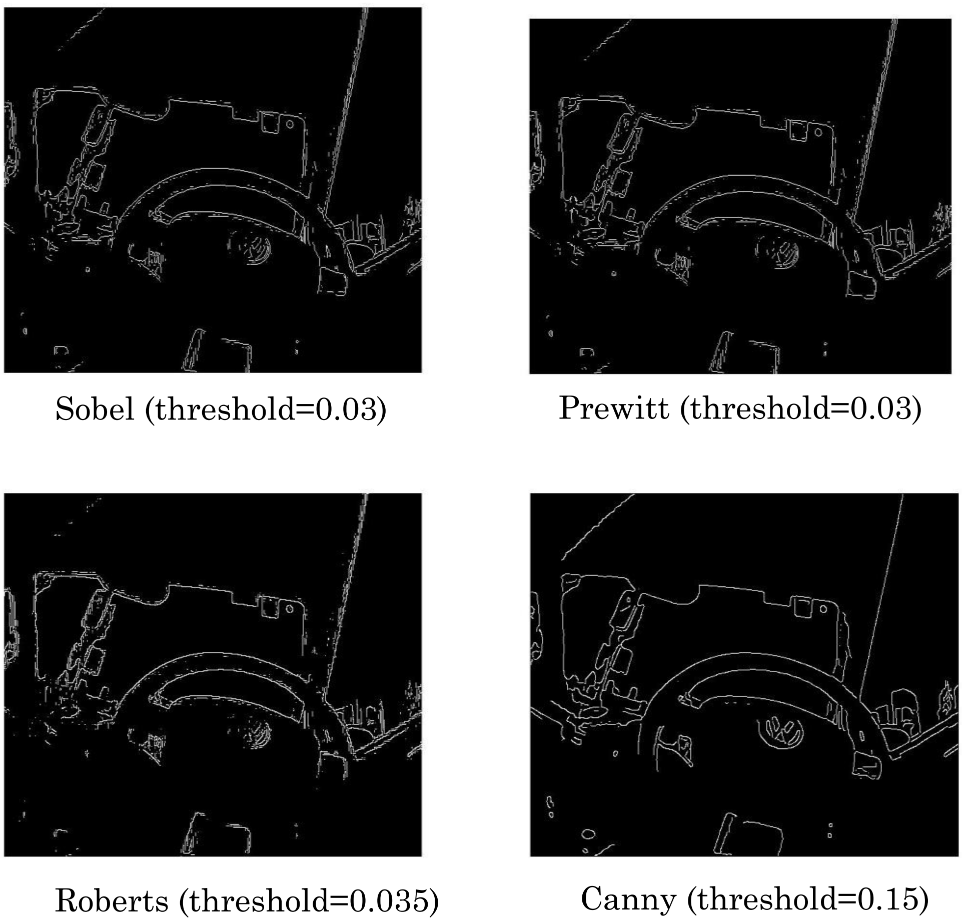
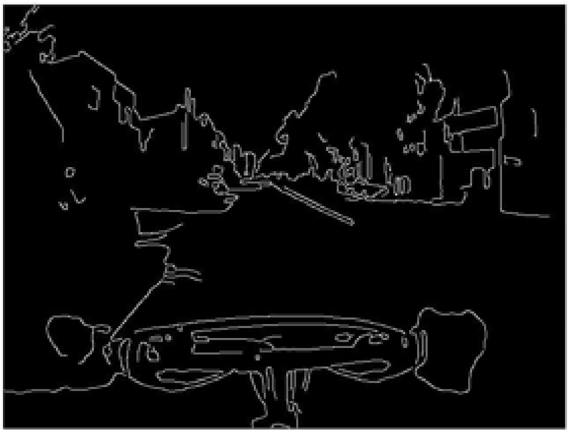


Figure 4.7 Performance of Different Operators for Edge Detection

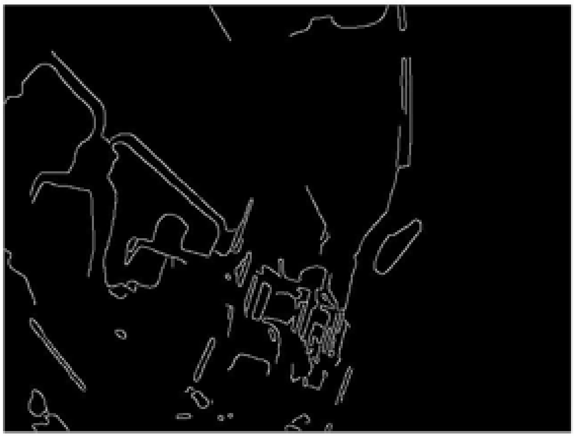
To choose a proper threshold is also a function of the environment. Generally speaking, it would be darker travelling in a car or on a bus than cycling on a bicycle. If a low threshold is chosen, there might be too much information in the cycling photos, which may report errors when mode is detected. For example, there might be some circles or curves on the roadside (e.g., traffic signs) when people are cycling. Because the critical feature for the car is a steering wheel, some circles or curves might be wrongly detected as "steering wheels".

On the other hand, if the threshold is too high, then the edge might not be detected for car trips. In other words, detecting car trips is more sensitive to the threshold than detecting bicycle trips. Therefore, a two-step method was applied. Firstly, a relatively high threshold (i.e., 0.3) was chosen. The requirement for this threshold was to identify the bicycle handlebar, and not identify any similar shapes for photos of car and bus trips. Figure 4.8 shows edge detection results of examples for all three modes with the threshold set to 0.3.

With the edge detection results, mode detection for bicycle was run first. There are 3,326 photos in total for the detection. A Hough transform was used to detect the lines in the photo so that the bicycle bars can be detected. In order to identify a handlebar, the length of the handlebar should be set as a threshold. A threshold with 25 pixels was set. Figure 4.9 shows a detection result for bicycles after detecting lines of the handlebars.



Bicycle



Bus

Car

Figure 4.8 Edge Detection Results by Canny Detector for Three Modes with Threshold=0.3

Figure 4.9 Mode Detection Result for Bicycles

Among the 3,326 photos, 159 photos were detected as “bicycle”. All the other photos were marked as “other than bicycle”. Then a similar rule used in the detection of mode change was used. Because the SenseCam takes images around every 22 seconds, if more than three (inclusive) successive photos are detected as “bicycle”, this successive “photo chain” represents a bicycle trip. If there are less than three successive photos marked as “bicycle”, these “bicycle” photos would be reclassified as “other than bicycle”. Although there would not be any mode change between bicycle, car and bus logically, the interval for taking photos may be too long to capture a case of mode change (i.e., a walking trip). So there still might be cases of mode change within a successive “photo chain”. Similarly, if there are no more than three successive photos marked as “other than bicycle” in a “photo chain”, they need to be reclassified as “bicycle”. By applying this rule, 25 more photos were marked as “bicycle”. Also one more case of mode change was detected.

The next step is to undertake edge detection again with a low threshold and run mode detection for car for all these photos. The threshold for the Canny detector used in this step was 0.15, in order to detect more details in the car (see Figure 4.10).

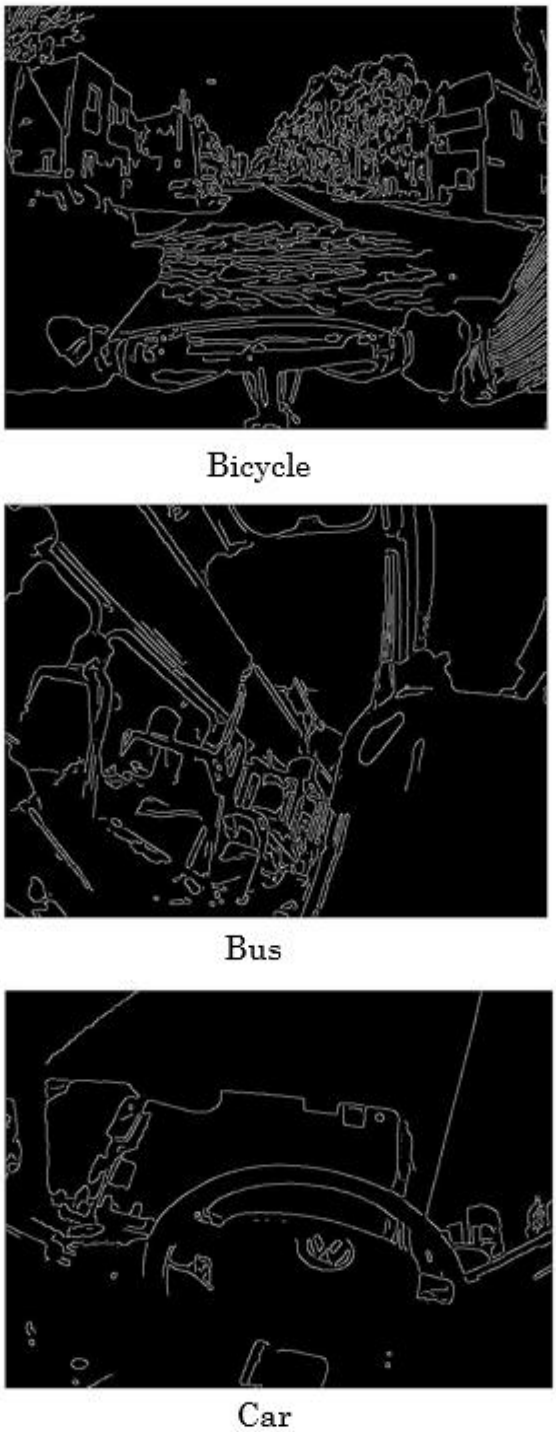


Figure 4.10 Edge detection results by the Canny detector for three modes with threshold=0.15

A Hough transform was used to detect the circle (i.e., steering wheel). Because different circles have different radii, a range needs to be determined. In Matlab, the unit for expressing the radius of a circle in an image is a pixel. According to the size of steering wheels for different cars, a range from 150 pixels to 300 pixels was chosen. Because of the angle of taking photos, a steering wheel in an image may not be a standard circle. Thus, there might be more than one circle being detected (see Figure 4.11). Also a value for sensitivity needs to be determined, because if the sensitivity is too high, it may detect some "circles" which were actually not circles. If the sensitivity is too low, then circles cannot be detected (see Figure 4.12).

Figure 4.11 Examples of Circle Detection

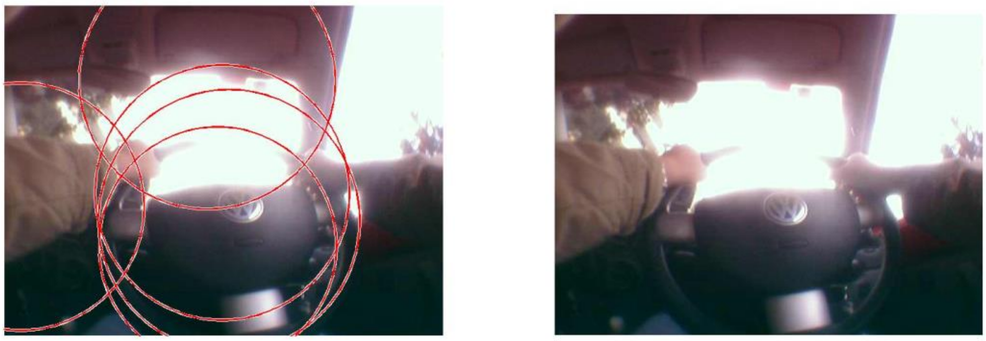


Figure 4.12 Circle Detection for Different Values of Sensitivity

Based on the results of circle detection, 2,801 photos were detected as car. A similar photo-chain rule was applied to identify a car trip. 22 more trips were reclassified as car after the rule was applied. Some photos may be detected as car in this step, but detected as bicycle in the previous step. This may arise, because the photos in this step have too much information about the edges of items, which could cause some errors for an outdoor trip. Circles on the road might be mistakenly detected as steering wheels. Therefore, if the result in this step is in conflict with the one in the previous step, the result from the previous step is used.

Although photos were detected individually, the result of car and bicycle detection was at the trip level. In total, there are 56 car trips that were detected, along with nine bicycle trips. Given that 75 were left after the detection of walk and train, and one more mode change was detected in image processing, the 11 remaining trips were bus trips. The mode distribution for all trips is shown in Figure 4.13.

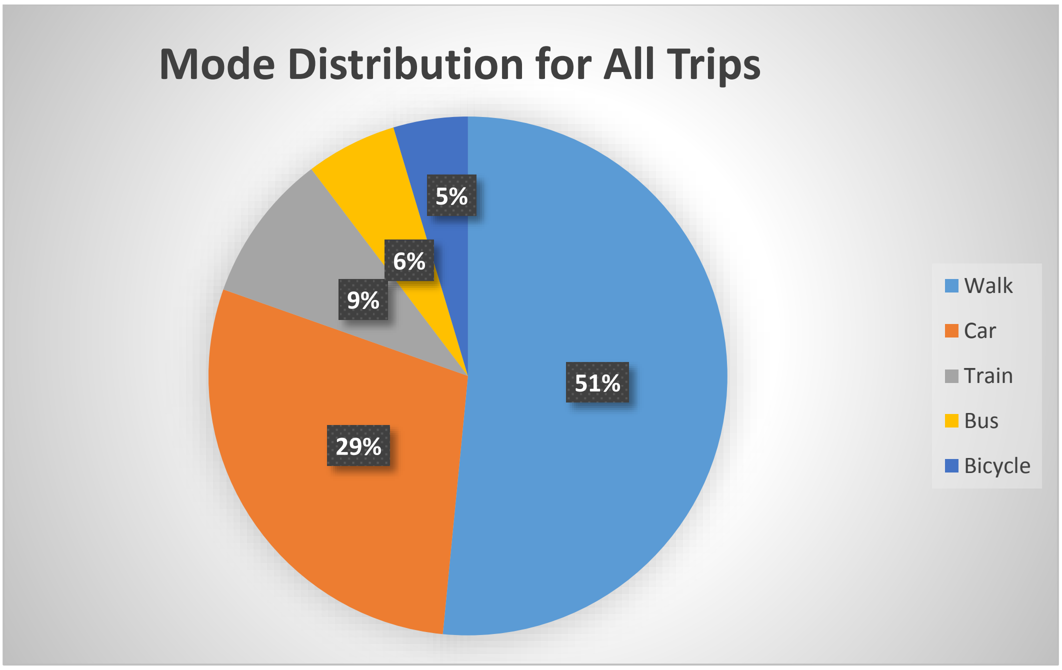


Figure 4.13 Mode Distribution for All Trips

4.3.3 Missing Trips

According to the analysis of ground truth, it has been shown that GPS devices may lose some data points. The method used in this study for data processing is based on both GPS devices and life-logging cameras, so after all the GPS data were processed, SenseCam images were used to find the missing trips.

The first task is to locate missing trips. In trip segmentation, some missing parts have been flagged when GPS records were linked with SenseCam images. There are two types of missing trips. One is caused by signal problems for GPS devices. For these missing trips, the destination of a trip usually does not match the next origin. The other type of missing trip is caused by respondents forgetting to carry the devices. For this type, the previous destination matches the next origin. It is necessary to investigate these flagged segments. Like the map editing process, this process can be called image editing, where the SenseCam Browser developed by the Nuffield Department of Population Health at the University of Oxford is used to visually investigate the information from the missing parts. Two tasks were involved in the image editing. The first was to add the missing trips, checking if the missing part includes one or multiple trips. Although the route of this trip may not be identified due to the loss of GPS data, travel duration and travel distance are still needed. Travel duration is the difference between start time and end time, which can be found from time-stamped images. Travel distance, however, can only be estimated from the difference between the previous destination and the next origin. The second task is to visually determine the travel mode for the missing trips from images.

Based on this investigation, 52 missing trips were found and added, which is about 20% of the total number of trips. By adding missing trips, the total number of trips identified for this dataset is 245. Table 4.16 shows the mode for the 52 missing trips.

Table 4.16 Mode for Missing Trips

	Number of trips	Percentage
Walk	44	84.6%
Car	3	5.8%
Train	5	9.6%

It appears that walk trips were easy to be missed. The reason is that some walk trips are too short to be recorded. Walk trips are also heavily influenced by the data quality. When data quality is low, single errors may be larger when the speed is low, and the errors would more easily generate a spurious trip. In that case, a real trip can be recorded as a spurious trip and mistakenly deleted by software or the process of map editing. There are no missing car or bus trips in this study.

4.3.4 Evaluation of the Case Study

Adding missing-trip information is the last task for the new process of trip identification and mode detection. The next step is to check the accuracy of the detection by comparing the result of this new method with ground truth.

4.3.4.1 Comparison between Ground Truth and Case Study Results

For research purposes, ground truth was obtained by visually checking the images from SenseCam with GPS information assistance. It was similar to the analysis in Chapter 4.1.

For trip identification, 246 trips were identified by the new process, while there are 258 real trips from ground truth. By comparison, all of the 12 trips were actually included in the identified trips but were not correctly split. Because the threshold dwell-time rule applied for the segmentation was 45 seconds, for those stops (not including mode change) less than 45 seconds, they were difficult to be identified. Although it should be rare that a real stop is less than 45 seconds for an activity, there are three stops based on the information from the ground truth. Also, a walking trip might be too short to be detected for a mode change. Sometimes the GPS signal issue could lead to a failure to detect a mode change. In the process of data cleaning, invalid data are removed based on the GPS data quality, but the data might be part of a real trip. Because of the removal of GPS data, there are not enough data points for identification. Seven trips were not split for this reason. There are also two short running trips that were not split. The purpose of the two running trips was actually mode change, and due to the speed and trip duration, the mode change detection process did not split them.

For the mode detection result, all the walking trips were detected correctly. There are 23 train trips according to ground truth. 18 train trips were correctly detected; another five, however, were not detected as train trips. The reason for not detecting train trips is that the GPS may have signal issues during the train trips, especially in the CBD in Sydney because the train travels underground. If the train trip loses some parts, it might be difficult for the software to detect the trip based on a GIS layer. None of these five trips were detected as car or bicycle in the image processing. Therefore, five trips were then classed as bus trips. Most of the car trips were detected correctly, while only one trip was not detected as car. Also, one bus trip was mistakenly detected as bicycle because the respondent just stood behind a horizontal handrail, which looks like the handlebar of a bicycle. Two bicycles trips were not detected, which were wrongly classed as bus trips. Table 4.17 shows the accuracy of detection for each mode.

Table 4.17 Accuracy of Mode Detection

Mode	The number of trips detected	The number of trips correctly detected	The number of trips from ground truth	Detection Accuracy
Walk	100	100	100	100%
Car	56	56	57	98.2%
Train	18	18	23	78.3%
Bus	11	3	4	75%
Bicycle	9	8	10	80%
Overall	194	185	194	95.4%

It seems that the largest difference between the number of detected trips and ground truth is from bus trips. This is because the sample size for this research is relatively small, and also the process actually does not directly detect bus trip but classes all the remaining trips not detected as other modes to be bus trips. Since the total number of trips at the trip level is relatively small, it would be useful to explore the detection accuracy for each photo. Table 4.18 provides the details of the result for image processing.

Table 4.18 Image Processing Result Evaluation

Mode	Image input	Mode correctly detected	Accuracy
Car	2,917	2,823	96.8%
Bicycle	208	184	88.5%
Bus	201	n/a	n/a

Because the results for bus trips were not directly detected by processing work, the table only shows the detection accuracy for car and bicycle trips. Overall, the accuracy is 96.2% (3,007 out of 3,125). The main reason for the incorrect detection is that the critical features (i.e., steering wheel and bicycle handlebar) are not very clear or are not captured in these photos. If the photo is too bright or too dark, the features are difficult to detect. Also, the bicycle handlebar might not be captured by the camera due to the movement of the cyclist. All the incorrect results were reported as “bus trips” by the processing software.

4.3.4.2 Comparison between Results from Existing Software and the New Method

Another comparison was also undertaken between the existing software and the new method to see if the new method improves the results. The existing G-TO-MAP software uses rule-based algorithms to detect trip ends, travel modes, and trip purposes. 120 seconds is used as the threshold of dwell time to identify a trip end.

For the purpose of the comparison, only trip end and travel mode results were compared. G-TO-MAP initially identified 191 trips out of 258, 33 of which were not split correctly. The existing processing method also involves a map editing procedure. While map editing fixed 14 trips for the issue of missing data, there are still 53 trips that could not be identified because there is no or limited data recorded by the GPS devices. Also, there is little clue for map editing to add those trips. Table 4.19 shows the comparison between the new approach and the existing method for trip identification.

Table 4.19 Comparison of Trip Identification between the New Method and the Existing Method

	Existing Method			New Method		
	Number of trips	Percent		Number of trips	Percent	
Exact trips identified initially	158	61.3%	66.7%	194	75.2%	95.4%
Trip fixed by editing work after initial processing	14	5.4%		52	20.2%	
Trips identified but not split	33	12.8%		12	4.7%	
Missing trips	53	20.5%		0	0%	
Total real trips	258	100.0%		258	100.0%	

In total, 66.7% of the total number of trips was identified by the existing method, 28.7% lower than the accuracy of the identification by the new method. The reason why the existing method only identified two third of the real trips is because missing trips comprised 20.5% of the total trips. It should be pointed out that the current method still can record about 20%-30% more trips than traditional diary reports. While there are still a number of trips not split correctly by both methods, there is no missing trip from the introduction of the life-logging camera in travel data collection.

For those trips that are correctly identified and split, mode detection results of both methods can be compared. While 140 trips were correctly detected by the G-TO-MAP software, which reaches a high accuracy level of 88.6%, the accuracy of the new method combined with GPS data processing and image processing is 6.8% higher. Table 4.20 specifically shows the comparison of the detection accuracy between the two methods by investigating in detail for each mode.

Table 4.20 Travel Mode Comparison

	Detection accuracy for the existing method	Detection accuracy for the new method
Walk	97.3%	100%
Car	88.6%	98.2%
Train	68.4%	78.3%
Bus	75%	75%
Bicycle	77.8%	80%
Overall	88.6%	95.4%

It appears that the accuracy of detection for car and bicycle by image processing is higher than for the GPS data processing. With the rule of the shorter threshold of dwell time and the approach of detecting mode change, walk and train trips can also be detected more accurately, because if more trips can be split correctly, the travel information for single trips can be more useful and accurate for detection.

4.4 Case Study for New Rules for Purpose Imputation

Travel data processing usually includes trip identification, mode detection and purpose imputation. Because the improvement has been made for trip identification and mode detection, improvement for purpose imputation should also be progressed. Some new rules for trip purpose imputation were also discussed in Chapter 3. In this section, an analysis to test if those new rules can be used to improve the purpose imputation results is reported. Because the data collected in Oxford and Sydney were not sufficient to test tours, a supplement of data collected in Ohio in the USA was used to show the results.

The Ohio Department of Transportation conducted the first GPS-only full-scale household travel survey in the USA in 2009 in the Greater Cincinnati region. Every member in the household over the age of 12 was asked to carry a passive GPS device for three days. After the collection, a prompted recall (PR) web survey was also conducted, in which respondents were assisted to recall their actual travel by receiving GPS-generated maps of where and when they travelled. The software known as G-TO-MAP was used to process all the GPS data. The rules suggested in Chapter 3 based on NHTS data were applied to the data from the Greater Cincinnati region survey to check the performance of these rules. The sample representativeness of the NHTS and the Ohio GPS survey was tested (See Tables 4.21 to 4.24). According to the sample size and data availability, household size, car ownership, the number of workers and household income are involved in the comparison. The results show that there are only a few notable differences in the distributions of household size, the number of workers, and the number of vehicles between the two datasets. Also, the large difference (7.21%) in households whose incomes are lower than $25,000 appear most likely to be the result of the 7.7% of households in the GPS survey that did not answer the income question.

The additional trip/tour information was applied in the GPS survey. In order to compare with the result from the PR data, all the trips in this study should be in both the GPS data and the PR results. After adding missing trips by map editing, there are 4,133 trips from the GPS data that can be used for analysis. Initially, compared with the PR results, which are currently regarded as "ground truth" in GPS travel surveys, the accuracy of trip purpose imputation for the processed GPS data is 58.7% (2,425 out of 4,133). Although the PR results are still not actual ground truth, they are the only resource that can be used in this study to check the accuracy.

Table 4.21 Comparison of Household Size

	GPS Data		NHTS Data		Percent Difference GPS / NHTS
Household Size	Frequency	Percent	Frequency	Percent	Percent
1 Person	669	32.5%	21632	29.23%	3.27%
2 Persons	696	33.8%	27385	37.00%	-3.20%
3 Persons	278	13.5%	10660	14.40%	-0.90%
4+ Persons	416	20.2%	14330	19.36%	0.84%
Total	2059	100%	74007	100%	

Table 4.22 Comparison of the Number of Workers

	GPS Data		NHTS Data		Percent Difference GPS / NHTS
Number of Workers	Frequency	Percent	Frequency	Percent	Percent
0 Worker	573	27.8%	24909	33.66%	5.86%
1 Worker	704	34.2%	27391	37.01%	2.81%
2 Workers	643	31.2%	18703	25.27%	-5.93%
3+ Workers	139	6.8%	3004	4.06%	-2.74%
Total	2059	100%	74007	100%	

Table 4.23 Comparison of the Number of Vehicles

	GPS Data		NHTS Data		Percent Difference GPS / NHTS
Number of Vehicles	Frequency	Percent	Frequency	Percent	Percent
0 Vehicle	91	4.4%	2267	3.06%	-1.34%
1 Vehicle	676	32.8%	19348	26.14%	-6.66%
2 Vehicles	809	39.3%	32143	43.43%	4.13%
3+ Vehicles	483	23.5%	20249	27.36%	3.86%
Total	2059	100%	74007	100%	

Table 4.24 Comparison of the Household Income

	GPS Data		NHTS Data		Percent Difference GPS / NHTS
Household Income	Frequency	Percent	Frequency	Percent	Percent
Up to $25,000	344	16.7%	17695	23.91%	7.21%
Over $25,000 to $50,000	450	21.9%	17918	24.21%	2.31%
Over $50,000 to $75,000	395	19.2%	12526	16.93%	-2.27%
More than $75,000	712	34.6%	25868	34.95%	0.35%
Don’t know/Refused	158	7.7%	n/a	n/a	
Total	2059	100%	74007	100%	

4.4.1 Validation by Using Additional Activity Information

According to the analysis of NHTS, there are three rules created in Chapter 3 to examine the processed GPS results and validate the results:

- Rule 1: If the duration is longer than four hours and the purpose detected from the GPS data is not work or education, this purpose should be suspected as being possibly wrong and the purpose may need to be redefined.

- Rule 2: If an education activity occurs before 5 am or after 8 pm, the purpose may need to be redefined.
- Rule 3: If the duration of a non-work or non-education activity is longer than 6 hours and the activity occurs before 9 am, the purpose may need to be redefined.

Because G-TO-MAP uses home addresses to impute return-home trips, which should be correct, none of the return home trips were validated. Based on Rule 1, there are 236 trips that are suspect. An in-depth analysis was conducted to visually examine these suspect trips. All of these trips were tested using Google Earth® and land use information (i.e., workplace address, school address, home address, and addresses of the two most frequently used grocery stores).

The trip purposes of 110 trips after testing remained the same as the GPS processed results (including 77 return-home trips). The results of the remaining 126 (=236-110) trips were modified. Specifically, 78 trips were changed from “other” to “work”; 23 trips were changed from “shop” to “work”; 6 trips were changed from “shop” to “education”; and 9 trips were changed from “other” to “education”. There were also 10 trips that were reassigned from either “shop” or “other” to “home”. Also, among those 126 trips, 73 trips could be validated by Rule 3. Only 5 trips met the condition of Rule 2. With visual examination from Google Earth®, all the trip purpose results of these 5 trips were modified. Table 4.25 shows the results of trip purpose validation based on these three rules. After the validation, the correct results of trip purpose imputation from the GPS data increased to 2,556 (=2,425+126+5), with an accuracy of 61.8%.

Table 4.25 Results of Trip Purpose Validation Based on Additional Activity Information

Type of Suspected Error	Number of Trips
Suspect trips (Rule 1)	236
Trips with no change after testing (Rule 1)	110
Trips with change after testing (Rule 1)	126
Trips changed by Rule 3	73
Suspect trips (Rule 2)	5
Trips changed after testing (Rule 2)	5

4.4.2 Validation by Using Tour-Based Information

As discussed in Chapter 3, tours from the NHTS data have been classified into 12 categories. Similarly, tour type classifications are undertaken based on the GPS data from the Cincinnati survey. From those 4,133 trips, there are 1,222 tours from the GPS results. Using the same classification as for the NHTS data, the proportion of each tour type is shown in Table 4.26.

Compared with the NHTS classification, Tour Types 11 and 12 from the GPS data are much higher (0.57% versus 0.12%, and 16.94% versus 6.56%). Also, Tour Types 3 and 6 are much lower (5.07% versus 11.51% and 11.46% versus 18.53%). Although NHTS, as a self-reported survey, is subject to memory mistakes and fatigue of respondents, the NHTS data still provides a useful benchmark for the distribution of tour types.

Therefore, the tours of Tour Types 11 and 12 should be examined. By checking the location on Google Earth®, these tours were revised by changing some trip purpose results, resulting in 75 “multi-part other” tours being assigned to other categories (in particular, 50 tours to complex shopping tours). Table 4.26 also shows the change of results before and after validation.

Table 4.26 Tour Type Classifications for GPS data

Tour type	Tour Description	Sequence	Number of Tours (Before)	Number of Tours (After)	GPS Percentage Before	NHTS Percentage	GPS Percentage After
1	Simple work tour	h-**w**-h	109	109	8.92%	12.80%	8.92%
2	Simple education tour	h-**e**-h	35	35	2.86%	2.69%	2.86%
3	Simple shopping tour	h-**s**-h	62	62	5.07%	11.51%	5.07%
4	Simple other tour	h-**o**-h	356	356	29.13%	31.17%	29.13%
5	Complex work tour (including composite and multipart work tours)	h – [**w**/o] – (– **w**/o –) – [**w**/o]– h	161	171	13.18%	7.95%	13.99%
6	Complex education tour (including composite and multi-part education tours)	h – [**e**/o] – (– **e**/o –) – [**e**/o] –h	32	34	2.62%	0.89%	2.78%
7	Complex shopping tour (including composite and multi-part shopping tours	h – [**s**/o] – (– **s**/o –) – [**s**/o] –h	140	192	11.46%	18.53%	15.71%
8	Complex work and education tour	h – [**w**/**e**/o] – (– **w**/**e**/o –) – [**w**/**e**/o] –h	21	21	1.72%	0.33%	1.72%
9	Complex education and shopping tour	h – [**e**/**s**/o] – (– **e**/**s**/o –) – [**e**/**s**/o] –h	14	15	1.15%	0.78%	1.23%
10	Complex work and shopping tour	h – [**w**/**s**/o] – (– **w**/**s**/o –) – [**w**/**s**/o] –h	78	91	6.38%	6.67%	7.45%
11	Complex work, education, and shopping tour	h – [**w**/**e**/**s**/o] – [**w**/**e**/**s**/o] – (– **w**/**e**/**s**/o –) – [**w**/**e**/**s**/o] –h	7	4	0.57%	0.12%	0.33%
12	Multi-part Other Tour	h – [**o**] – (–/o –) – [**o**]–h	207	132	16.94%	6.56%	10.80%

It would be useful to test to see whether the distributions of the GPS tours and NHTS tours are significantly different from each other, and also to determine whether the changes in tour purposes increased the similarity of the two distributions. Unfortunately, there are some difficulties in doing this. The chi-square test is rejected because the values from the chi-square test are heavily influenced by the magnitude of the values of the numbers of tours and because the differences in sample size between the Cincinnati GPS survey and the NHTS are too large. Alternatively, the Kolmogorov Smirnov (K-S) test is the best available test for this analysis.

The K-S test statistic D_n is defined by

$$D_n = \sup_x |F_n(x) - F(x)|$$

Where $F_n(x)$ is an empirical cumulative distribution function; $F(x)$ is a given cumulative distribution function; and n is the sample size.

The K-S test (see Table 4.27) also shows the improvement of results after using additional activity information and tour-based information. D_n for the GPS results before validation is 0.1230. Using additional activity information and tour-based information, D_n in the K-S test is reduced to 0.1219, which means that the difference of distributions between GPS results and the NHTS data has been reduced. Given that the D value is 0.375 at a significance level of 0.05 for 12 categories, both GPS results are not significantly different from the NHTS records. The validation for the GPS results also removed some large values of D_i, thereby decreasing the K-S test value.

Table 4.27 Kolmogorov-Smirnov Test

Expected	Cumulative Percentages	Before	Cumulative Percentages	D_i	After	Cumulative Percentages	D_i
12.80%	12.80%	8.92%	8.92%	0.0388	8.92%	8.92%	0.0388
2.69%	15.49%	2.86%	11.78%	0.0371	2.86%	11.78%	0.0371
11.51%	27.00%	5.07%	16.85%	0.1015	5.07%	16.85%	0.1015
31.17%	58.17%	29.13%	45.98%	0.1219	29.13%	45.98%	0.1219
7.95%	66.12%	13.18%	59.16%	0.0696	13.99%	59.97%	0.0615
0.89%	67.01%	2.62%	61.78%	0.0523	2.78%	62.75%	0.0426
18.53%	85.54%	11.46%	73.24%	0.1230	15.71%	78.46%	0.0708
0.33%	85.87%	1.72%	74.96%	0.1091	1.72%	80.18%	0.0569
0.78%	86.65%	1.15%	76.11%	0.1054	1.23%	81.41%	0.0524
6.67%	93.32%	6.38%	82.49%	0.1083	7.45%	88.86%	0.0446
0.12%	93.44%	0.57%	83.06%	0.1038	0.33%	89.19%	0.0425
6.56%	100.00%	16.94%	100.00%	0.0000	10.80%	100.00%	0.0000
			Dn	0.1230			0.1219

Because there is not a natural order to the tour types, a second test was run in which the tour types were ordered from the most-frequently occurring to the least-frequently occurring in the NHTS data. The result of this was slightly higher, but still non-significant values of the K-S statistic, with the before value being 0.1943 and the after value declining to 0.1518. Again, these values are well below the 5 percent significance value of 0.375, but also show a more marked decrease from the before situation to the after situation.

From these tests, it can be concluded that the distributions were initially not significantly different according to the K-S test. Also, while the distributions were still not significantly different after the adjustments, the values had become closer.

Within the 75 “multi-part other” tours being assigned to other categories, the trip purposes of 191 trips were corrected. The number of trips whose purposes are correctly imputed is correspondingly increased to 2,747 trips (=2556+191), and a final accuracy of trip purpose imputation is 66.5 percent (2,747 out of 4,133 trips). Table 4.28 demonstrates the final results.

Table 4.28 Final Results of Validation

Correction	Number of Trips (Percent)
Initially correct trips in terms of purpose imputation	2,425 (58.7%)
Correct trips after activity information is applied	2,556 (61.8%)
Correct trips after tour-based information is applied	2,747 (66.5%)

4.5 SUMMARY

In this chapter, all the issues mentioned in Chapter 3 were analysed. Findings and results based on the method introduced were discussed. The analysis of ground truth proved that life-logging cameras can help to obtain ground truth, especially because they can find missing trips that GPS devices fail to record. The result of this analysis also suggests that walking trips are more likely to be missed for GPS records.

The analysis of the time interval of recording data suggests that using five seconds as an interval to record data seems to be the best option for trip identification, because it can still record important information of trip ends for the identification, and also can reduce the total number of data points. However, it might be premature to conclude that using a five second interval would still get an accurate result of mode detection and purpose imputation. The reason is that detecting modes and purpose needs more detailed information for a trip that a longer time interval may lose. Lack of data points may also lose the detail of the travel route, which will cause a problem when GIS information is used for public transport detection.

In the area of GPS data processing, the threshold of dwell time is always critical to identify a trip end. This study tested different options to conclude that a threshold between 45 seconds and 60 seconds would be the optimal option, because it can detect most of the short stops, and would not generate too many spurious stops. In this study, a threshold dwell time of 45 seconds was applied in the analysis for data processing.

A new method for collecting and processing the travel data was introduced in Chapter 3. This chapter also shows results by applying this new method to a case study in Sydney. Based on the results, life-logging cameras have potential to be used in household travel surveys to improve data quality. The new method combined the procedure of trip identification and mode detection to identify more cases of mode change. All the trips were identified by the new method although a few trips were not split correctly. Dedicated GPS devices were still used in this study because GPS data are still important for collecting travel information (e.g., travel speed, locations, routes, etc.).

Walking trips and train trips were detected by GPS data. Car and bicycle trips were automatically identified by the information obtained from GPS data and the images from SenseCam cameras, with overall above 95 percent accuracy. An image processing procedure was applied for the detection. Also, the concept of a "photo chain" can help to fix some mistakes in detection. Comparing to the existing method, the accuracy of trip identification and mode detection by applying the new method is higher.

As an entire processing procedure, this study also introduced some new rules that involved additional trip information and tour information for trip purpose imputation. From the results, the proposed additional information can help improve the accuracy of trip purpose imputation. Specifically, a rule for activity duration of work/education trips, a rule for the time when work/education trips occur, and also a tour-based trip chain were suggested. In total, the accuracy of purpose imputation is increased by approximately 8% for the dataset used in this study.

The key points of this chapter are:

- The result of testing a threshold of dwell time suggests that 45 seconds performed better than other options in this study;
- GPS data can be sampled by every five seconds to reduce the processing time for trip identification;
- Life-logging cameras can be used in travel data collection to obtain ground truth and also help to identify travel modes;
- The new approach which combines trip identification and mode detection can improve the total results of both steps; and
- Additional travel information was suggested to add into purpose imputation. The result shows the accuracy can improve 8%.

5 CONCLUSION

Chapter 1 of this thesis introduces the background of this research area, followed by a systematic review of the literature in Chapter 2. Based on the research gaps discussed in the review, Chapter 3 and Chapter 4 documented the application of a new procedure for travel data collection and data processing. In this chapter, Section 5.1 summarises the results and findings of this research. Section 5.2 highlights the main contributions based on the findings. Similar to most research, there are a few limitations in this study, which are discussed in Section 5.3, and Section 5.4 provides suggestions for future work in this area.

5.1 SUMMARY OF RESEARCH RESULTS AND FINDINGS

This study has addressed the research gaps mentioned in Chapters 1 and 2. In the analysis of ground truth, this study compared the results from SenseCam and GPS devices. It concluded that life-logging cameras can be used to help find ground truth, especially for finding the missing trips that GPS devices do not record, and identifying travel modes. Ground truth then can be used for the validation of travel data processing. Also, with SenseCam images, the performance of GPS devices was investigated in detail in this study. In general, GPS devices may miss approximately 20-25% of trips. Specifically, GPS data are more likely to be missing at the beginning of a trip due to cold starts and for short-duration trips. Those missing trips are more likely to be walking trips, which may not have a large impact on surveys of vehicular travel. This research suggests that trips recorded by GPS devices may need to be split when a short duration trip occurs at the beginning or at the end of the whole journey or when a short duration activity occurs during the whole journey.

Based on the ground truth obtained by life-logging camera and GPS devices, this study also undertook a number of tests to improve the criteria of identifying trips/segments. The time interval for recording data was tested. According to the results, a 5-second option seems to be the best option for trip identification for this study because more new real trips were identified; however, the comparisons of mode and purpose detection indicate that one-second data can provide more detailed travel information and more accurate mode and purpose detection results. This suggests that data should continue to be collected at a one-second interval, but processing for trip identification could potentially sample the data, using five-second intervals between data points.

This study also tested the value of the threshold of dwell time that defines when a trip ends. Currently, most research uses 120 seconds as the threshold of dwell time. This study suggests that this may lose about 20% of the real stops. While many of those real stops can be fixed by reducing the threshold, more new spurious stops will be created at the same time. Therefore, the stop-time rule might be tightened, but the extent of tightening will depend on the relative costs of splitting trips by map editing, versus deleting spurious stops (i.e., combining trips) by map editing. Considering the trade-offs between the number of new real stops and spurious stops, and between the cost of adding real stops and deleting spurious stops, it is concluded that the 45-second option is the best option for the dwell time according to the data collected in Oxford. In terms of travel modes, people are more likely to undertake a short time activity when they are walking, and those short duration activities are usually shopping, mode change and pick-up or drop-off. The test also suggests that some changes might be made to loosen rules for trip identification.

Based on the case study in Sydney, the new procedure for collecting and processing the travel data was tested. About 95 percent of the trips were correctly identified by the new procedure. The other 5 percent of the trips were actually recorded by the devices but were not correctly split. Compared with an existing procedure (G-TO-MAP), which appears to be one of the most accurate methods that is currently available, the trip identification accuracy is increased by almost 30 percent, taking the missing trips into account. The new method, which combines the procedure of trip identification and mode detection, identified more cases of mode change. It needs to be mentioned that dedicated GPS devices were still used in this research because GPS data are still important for collecting travel information (e.g., travel speed, locations, routes, etc.).

While mode detection is combined with trip identification in the new procedure, investigating the accuracy specifically for mode detection is still necessary. In the new procedure, walking trips and train trips were detected by GPS data only. Car and bicycle trips were automatically identified from the information obtained from GPS devices and the images from SenseCam cameras. An image processing procedure was applied for the detection. Also, the concept of a “photo chain” was used to help fix some mistakes in image processing. From the results of mode detection, walk trips can be detected with 100 percent accuracy, followed by car trips (98.2 percent). For all modes, the overall accuracy is 95.4 percent. The accuracy to detect a car from a single photo is about 96.8 percent, while 88.5 percent of the photos for bicycle trips can be correctly detected. By comparing with an existing method, the accuracy of mode detection by applying the new method is 7 percent higher than the accuracy by using the existing method.

In terms of trip purpose imputation, this research introduces a number of new rules that involve additional trip information and tour information for trip purpose imputation. The proposed additional information can help improve the accuracy of trip purpose imputation. Specifically, a rule for activity duration of work/education trips (i.e., rule 1: if the duration is longer than four hours and the purpose detected from the GPS data is not work or education, this purpose should be suspected as being possibly wrong and the purpose may need to be redefined), a couple of rules for the time when work/education trips occur (i.e., rule 2 and 3: if an education activity occurs before 5 am or after 8 pm, or if the duration of a non-work or non-education activity is longer than 6 hours and the activity occurs before 9 am, the purpose may need to be redefined), and also a tour-based trip chain were applied in this study. A GPS-only survey in Ohio in the US was used for the test. In total, the accuracy of purpose imputation was increased by approximately 8 percent in our case.

This study also pointed out that although GPS surveys may still have some issues currently, it is clear that GPS devices can record more accurate travel information than self-reported diaries, and GPS surveys have become more reliable and cheaper nowadays for data collection. With the development of new technology, more new devices could be introduced in travel data collection, along with GPS units, to collect more accurate data.

5.2 MAIN CONTRIBUTIONS

GPS surveys are increasingly accepted and applied for travel data collection. To obtain more accurate travel data, a number of methods of processing GPS data have been developed during the past decade. This study has a number of original contributions to the literature and practical data collection.

- This thesis systematically reviewed the approaches for identifying trip ends, detecting travel modes, and inferring trip purposes. Based on the review, both advantages and disadvantages for different approaches were discussed. Research gaps that currently exist were pointed out.
- This thesis investigated the issue of ground truth. Life-logging cameras were introduced for the first time in travel surveys. It has been shown that these cameras can help improve data quality.
- This thesis tested the time interval of recording data to show the potential to reduce the number of data points and further save processing time.

- The threshold of dwell time was tested for the first time, which can help identify more short duration stops.
- An approach combining the steps of trip identification and mode detection was suggested. By this approach, more mode changes can be identified and trips can be identified not only based on the original GPS inputs (e.g., speed, duration of stops, etc.), but on the result of mode detection also.
- A new procedure of processing data from GPS and life-logging cameras was suggested and tested. Image processing was applied to detect travel modes for the first time. In addition, the impacts of signal issues (especially signal loss) from GPS devices are reduced by applying the life-logging camera data.
- The map editing process in the new procedure is much easier than the existing process, which can therefore reduce a great amount of time
- For trip purpose imputation, additional rules were tested and shown to improve the results of purpose imputation.
- This thesis applied tour-based information to assist trip purpose detection for the first time. Travel mode and trip purpose were typically identified from a single trip. Tour-based information identified a number of trips as a "trip chain". Using the logical sequence of the trip chain, the accuracy of purpose imputation can be increased.

Existing studies usually use arbitrary rules to determine GPS data frequency and identify trip ends. This thesis tested different options for these rules and suggested best rules for this study. By using the new rules, more short-stop trips can be identified, which would be useful when researchers or planners need to analyse trips of serving passengers. Also, this study proved that one-second data may not be necessary for trip identification.

There is very little research that has addressed the ground truth issue in the literature. Most studies were limited in how to obtain ground truth. Some studies used travel diaries to train their learning system for mode detection, which would reduce the accuracy of the processing results. This research provided a new method to pursue ground truth which could be used in the future, especially for studies which need training data. In addition to that, ground truth can help report the correct accuracy of data processing for each study.

Trip identification and mode detection are typically separated in GPS/Smartphone data processing. The overall accuracy of mode detection is associated with trip identification accuracy. If trips cannot be identified correctly, travel modes detected for those trips are incorrect. In this study, these two steps were combined into one, so mode detection results can also correct some results in trip identification. The overall result was generated together from trip identification and mode detection.

Little GPS research has provided a proper method to deal with missing data due to GPS signal issues. The main reason is that there is very limited information that can be used to impute missing parts. This study introduced life-logging camera to visually review the missing data in GPS data streams. The new technology can fill the missing gaps between trips. The common inputs used in current research in purpose imputation are land use and the addresses of homes, work places and shops. Different from existing studies, this research suggested that more information needs to be added as inputs. The result from this thesis proved that additional information can improve the purpose imputation result.

5.3 LIMITATIONS

There are several limitations to this study. The sample size is relatively small for the tests and the case study for the processing of trip identification and mode detection. Because only five life-logging cameras were avaible to use in Oxford, and only one camera was avaible to use in Sydney, a small sample was drawn for research purpose in order to obtain ground truth, but the number of trips, especially the number of trips for each mode is small.

Secondly, bus trips were not compared between GPS processing results and ground truth because the GIS bus network was not available in Oxford. Another limitation is from the device. While SenseCam helped identify missing trips from GPS devices due to signal issues, SenseCam also missed some trips or stops because of low light or the lens accidently being covered by respondents. Better instructions need to be provided to the respondents. Because, with the first generation of life-logging cameras, there is no GPS module in the camera, participants had to carry both devices for all the survey period, which might be burdensome. Also, even with the new generation camera which is equipped with a GPS module, cameras currently cannot record GPS information as frequent as dedicated GPS devices and cannot record speed and direction as dedicated GPS devices do. Hence, respondents will still be needed to carry dedicated GPS devices, which therefore influence the response rate and the data integrity.

Limitations also exist in the research on trip purpose imputation. First, the basis of the additional travel information (i.e., activity duration, the time when activities occur and the distribution of tour types) were derived from NHTS data, which is subject to the problems of self-reported surveys. Second, the PR results were used as ground truth for this test because life-logging cameras were not available for that study. PR results have been shown not to be real ground truth, which could lead to a problem where GPS results might be correct while PR data show different results. Bohte and Maat (2009) found that people struggle a lot with a PR survey when they need to add/split a great number of trips, and as a result they may leave the wrong trips in the PR results. But in the Ohio data, PR is the best source to validate the data.

There is no study that has been undertaken for the comparison between life-logging cameras and GPS records, while Kelly (2013) has compared SenseCam images with travel diaries. As mentioned in Chapter 2, the missing trips he found from SenseCam were more than this study. Given his sample size was also small, a larger sample may need to be tested in the future to provide more details of the performance of life-logging cameras.

5.4 FURTHER DISCUSSION

There are several additional issues that can be discussed. As suggested above, the time interval to record data could be changed especially for trip identification. One might use a 5-second interval by drawing a sample from one-second data for trip identification, but there could be at least five different samples, depending on the starting point. For example, for a trip being made from 16:00:01 to 16:06:40, one can draw a sample from 16:00:01, and take every fifth point after this start point until the end of the trip. One also can draw the sample from 16:00:02, 16:00:03, 16:00:04, or 16:00:05. Therefore, all the five samples can be drawn and the results from all the five possible samples can be compared.

In addition, similar to GPS loggers first being applied in travel data collection, it is questionable whether wearing SenseCam could be a new burden for participants. However, because SenseCam is a passive digital camera, it is relatively easy for participants to carry it.

Ethics (e.g., privacy) is another issue of carrying cameras, and most participants will be concerned about this issue. Kelly et al. (2013) developed an ethical framework for wearing the cameras in related research. They suggested that a good framework can help solve ethical problems. This framework includes the preparation of documents for surveyors and instructions for the respondents. Also, the manufacturer built in a "pause" button to give respondents an opportunity to stop taking the photos for seven minutes for the first generation device, i.e., SenseCam. There has not been any research on the publics' willingness to wear this type of camera for travel data collection, which needs to be done in the future when larger samples are collected.

Also, it is still unclear whether the general public are willing to carry life-logging cameras. Wearing cameras when people travel may be intrusive for both survey participants and those people who are captured by the cameras. The acceptability of this new device still needs to be investigated, especially for different groups of people.

The next step of this research is to try to identify the critical features for other modes besides car and bicycle. Since photos have been shown to be able to provide more reliable and accurate results, photos could be used to detect all modes. Car occupancy is another topic for future research. Because the view from a car driver and a car passenger is different, identifying the number of persons in a car is possible. Similarly, a study of purpose imputation based on life-logging cameras needs to be undertaken. Photos provide much more detailed information about activities. While identifying the critical feature for activities is extremely complicated and difficult, it is still worthwhile investigating if activities can be imputed directly from photos. Also, another approach (i.e., machine-learning systems) may be applied to process images automatically.

The newest generation of life-logging cameras have a GPS module built in. However, researchers/consumers do not have full access to the GPS data. Data are currently uploaded and stored in the Cloud from the company who designed and manufactured the cameras. Nevertheless, it is possible to have a life-logging camera with full access to GPS data in the future. If

GPS devices and cameras can be combined as one device, then the respondents would not experience increased burden to carry the life-logging cameras, and the data quality for travel surveys could be improved. Passive digital cameras can be used more widely in transport research. For instance, research on cyclists can collect more accurate bike trips by cameras because the bicycle bar is clearly shown in the photos; crowd research also could benefit from the photos captured by passive cameras on public transport and in crowded pedestrian areas. With the benefits that cameras bring, it can be expected that more studies will be conducted by using the new generation cameras in the transport area in the future. Furthermore, besides using the life-logging cameras, there is another potential direction for travel data collection in the future, which can deal with the current problems of GPS surveys. Bolbol et al., (2010) have proposed Geoweb 2.0, crowd sourcing and user generated content, as a possible way to collect data and enable travellers to upload their trips directly to the web to see them.

5.5 SUMMARY

This chapter summarised the findings in this thesis, and discussed the limitations of this research and provided a number of thoughts about future work. The key points of this chapter are:

- The approach suggested in this study filled a number of research gaps mentioned in Chapter 2. Overall, the new procedure can raise trip identification accuracy by almost 30 percent, taking the missing trips into account. The accuracy of mode detection and purpose imputation increased by 7% and 8%, respectively.
- This study provided two directions to the literature: improving the current methods and using a new technology and processing procedure for travel data collection.
- Sample size is the main limitation in this study. Also, ethical issue would become the main obstacle for people to use life-logging cameras in travel surveys.

- Image processing could be undertaken for purpose imputation. Since the images are shown visually, the result could be better than GPS processing.

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