DATA VISUALIZATION IN TRAVEL AND PHYSICAL ACTIVITY STUDIES

Michelle Lee, Jean Wolf, Marcelo Oliveira and Mary Kaiser

Michelle Lee (mlee@geostats.com)
Jean Wolf (jwolf@geostats.com)
Marcelo Oliveira (moliveira@geostats.com)
Mary Kaiser (mkaiser@geostats.com)

GeoStats LP
530 Means St, NW, Suite 310
Atlanta, GA 30318 USA
Phone: 404-588-1004
Fax: 404-588-1227

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ABSTRACT

Over the past decade, Global Positioning System (GPS) data collection has been used in tandem with traditional travel survey methods as researchers and practitioners seek technology solutions to address issues with respondent burden and data accuracy. Relatively recent advancements in GPS receiver and battery technology have generated a range of reasonably priced, small, and power-efficient wearable GPS data loggers that can be deployed to each person in a participating household. Also during the past decade, the use of small wearable accelerometers has become a standard measure of physical activity in many health studies. It seems almost inevitable that the dual deployment of both technologies would lead to new and interesting measures of physical activity and travel. This paper discusses the background of physical activity studies with respect to measurement and visualization, then moves on to focus on joint travel behavior and physical activity measures and the methods used to visualize these metrics as implemented in several recent studies.

INTRODUCTION

The use of Global Positioning System (GPS) data collection in tandem with traditional travel survey methods and physical activity studies has become commonplace over the last decade. Within the United States (US), passive GPS instrumentation in travel surveys typically has taken the form of in-vehicle deployments due to the size, form factor, and power demand constraints of early wearable GPS data logging devices. However, recent advancements in GPS receiver and battery technology have generated a range of reasonably priced, small, and power-efficient wearable GPS data loggers. Due to these recent enhancements, GPS logging devices can now be deployed to each person in a surveyed household, essentially mimicking the one-diary per person approach in traditional travel surveys, without increasing respondent burden.

Accelerometer technology, which allows researchers to objectively assess the intensity of physical activity, has led to the widespread use of these passive activity monitors in physical activity studies over the past decade. With the advent of wearable GPS devices, health researchers and urban planners have combined these two technologies within the past five years in an attempt to measure the spatial dimension of physical activity.

The prevalence of both GPS and accelerometer technologies has led to an increased need to analyze and present data collected in tandem by these devices visually. This paper touches on the background of household travel surveys, focuses on physical activity studies with respect to measurement and visualization, then explores joint measures and methods used to visualize these metrics as implemented in several recent studies.

BACKGROUND

Since the first GPS-enhanced travel survey, software has been needed to process GPS data into trip-level details. Given the inherent spatial and temporal components of GPS data, the development of this software has included a significant Geographic Information System (GIS) component for both visualization and analysis of travel behavior. These GIS-based software tools have proven incredibly useful to project analysts, clients, and study participants, as they allow for more accurate processing, visualization, and understanding of the data.

The objective measurement of physical activity has been a challenge for researchers for many years. Self report and observational methods are common, but are subjective and, therefore, not always accurate. Objective monitoring of physical activity was made possible with the introduction of pedometers. In the last ten years, accelerometers, which can record step count along with the intensity of physical activity, have become the standard for objective measurement of physical activity. Accelerometers also allow researchers to customize activity thresholds for different age groups and body types and to parse that data into bouts of activity.

When health-monitoring sensors are deployed in tandem with wearable GPS loggers, additional variables (such as physical activity levels or step counts) can be matched to the GPS data using time stamps. GIS-based software tools can then be employed to conduct spatial, as well as temporal, analysis and presentation of physical activity data simultaneously with the GPS-based travel details – providing a rich, robust dataset ripe for analysis and visualization.

Household Travel Surveys

Since 1996 when the US Federal Highway Administration sponsored the first GPS-enhanced travel survey pilot study, there have been scores of studies testing or implementing the use of GPS devices to either augment or replace traditional travel survey methods. This application for GPS technology enables the collection of spatial and temporal details of travel, with accuracy levels for trip start and end locations, trip start and end times, travel routes and speeds, trip durations and distances never before attainable using self-report methods. The spatial and temporal details inherent in GPS data lend themselves well to visualization of household travel patterns. Figure 1 shows a typical GPS point trace in context of the local street network. When a background aerial is added behind a GPS trace, a trip end pattern that may have been unidentifiable can easily be recognized as typical parking lot search behavior.

Figure 1: Typical parking lot search behavior

This paper assumes that readers have a basic knowledge of GPS applications in travel surveys and, therefore, focuses on physical activity measurement and the visualization of joint measures for travel behavior and physical activity. Reference materials for GPS measurement and visualization for household travel surveys can be provided upon request.

Physical Activity Studies

Physical activity (or lack thereof), from a health standpoint, can denote several key individual factors, including risk of chronic disease, obesity, and quality of life, as well as societal factors, including social and economic cost of physical inactivity. Physical activity occurring during waking hours is considered in two contexts: recreational, concerning free-time activity, and utilitarian, involving everyday lifestyle-integrated activity (Caspersen, C., *et al.*, 1985)

Levels of physical activity are indicative of an individual's overall health (Kahn, 2001). Accuracy in the measure of energy expenditure is recognized as an important piece of physical activity; however, an international consensus statement recognizes muscular strength, motor fitness, and metabolic fitness, among others, as distinct physiological markers in determining physical activity (Bouchard *et al.,* 1994). Analysis of physical activity can become more visual, and therefore more descriptive, through the process of activity recognition. Similarly, the measurement of health and the practice of health promotion becomes more straightforward through the visualization of physical activity and energy expenditure. Pärkkä, *et al*., (2007) recently completed a pilot study that found correlation between physical activity sensor signals and the intensity associated with various physical activities using metabolic equivalents. A recent study conducted by Ermes, *et al*., (2008) explored methods for activity identification in both controlled and uncontrolled settings using accelerometers.

Physical Activity Measurement Methods

Past studies that attempted to measure physical activity have used a range of subjective and objective methods to acquire useable data. (Mackett, *et al.,* 2007; Rodriguez, 2006; Tudor-Locke, 2001). The most commonly used methods include travel diaries, pedometers, heart-rate monitors, and accelerometers; a summary of these methods with respect to various attributes can be seen in Table 1.

Table 1: Comparison of Different Activity Data Collection Methods

	Diaries	Heart Rate Monitors	Pedometers	Accelerometers
Cost to Implement	Low	Moderate	Low	Moderate to High
Measurement Type	Subjective	Objective	Objective	Objective
Accuracy of Data	Varies Greatly	High when coupled with basic health data	High	High
Usefulness of Data	Varies greatly - all data subjective, difficult to do cross comparisons	Useful, but limited based on environmental factors	Useful, but limited to step count	High, although dependent on calibration
Ease of Data Analysis	Often requires interpretation and standardization	Data analysis can be automated	Data analysis can be automated	Data analysis can be automated

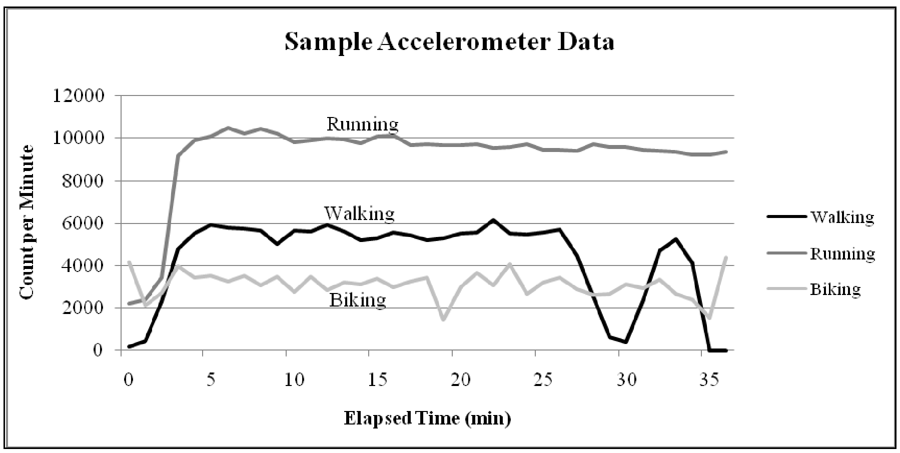
*Travel Diaries***.** Methods of self-reporting through travel diaries are often the most efficient and convenient forms of physical activity data collection. Also, researchers can request detailed information on bouts of physical activity, including frequency, duration, type of activity, perceived physical exertion, and context. However, trip misreporting can have significant effects on results and conclusions of a study being conducted. Accounting for imperfections in self-reporting is difficult because of the individualized nature of results. Typically, travel diaries provide quantifiable nominal data based on the reported information.

Pedometers. Mechanical pedometers have been used internationally in physical activity studies for over thirty years. Typically, pedometers rely on lever arms that move up and down with walking or running motion, closing a circuit at one instance per step. Pedometers are typically worn on the hip or foot. Data is presented as accumulated steps. Newer pedometers are able to record accumulated steps in terms of a time frame or with a time stamp. This gives researchers time-relative activity counts that provide information on the frequency and duration of physical activity when using pedometers. (Tudor-Locke, 2002).

*Heart Rate Monitors***.** An individual heart rate provides a measure of intensity and exertion, but must be calibrated for each participant individually. When properly calibrated the frequency, intensity and duration of activity can be easily obtained (Rowlands, 2007). Heart rate monitors require that a strap be worn around the torso and are therefore more invasive than other objective monitoring devices. Since the authors have not been involved with any studies using these monitors, no further discussion is provided within this paper.

*Accelerometers***.** Accelerometers are similar to pedometers, but in addition to step count they provide the ability to measure intensity in physical activity. The device works by detecting body movement in terms of acceleration, which can then be interpreted into measurement of intensity in activity (Chen and Basset, 2005). The device is typically worn on the hip. Technical considerations involved in choosing accelerometers include: the type of accelerometer to be used (e.g. uniaxial/biaxial/triaxial, user interface, storage capacity, "cool factor"), the number of accelerometers used per participant at one time, the position of the accelerometer on the body, the epoch length, and the study length (Trost, *et al.*, 2005). The studies presented in this paper were conducted using the ActiGraph (sold by ActiLife, LLC, Fort Walton Beach, FL) accelerometer, which provides three dimensions of measurements and a pedometer to compliment the measure of acceleration. Figure 2 shows accelerometer data collected during various modes of self transport by a GeoStats employee.

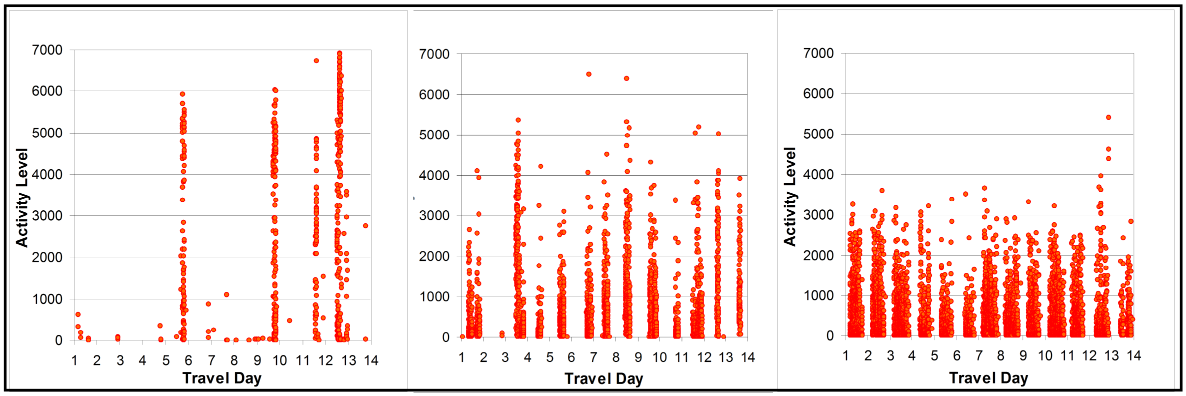
Figure 2: Accelerometer data for various modes of self-transport ***(Source: GeoStats)***



Accelerometers provide accuracy in recognizing position change and gait patterns associated with dynamic activity, but at times can underestimate the activity levels associated with stationary and complex physical activity, such as weight lifting or cycling (Matthews, 2005). Physical activity data collected from accelerometers are dimensionless data and can be difficult to interpret when isolated, but this allows researchers to calibrate data for specific study samples or populations for more thorough analysis. Different thresholds for moderate to vigorous physical activity can be developed for varying populations, making the data comparable across otherwise dissimilar populations.

Figure 3 shows a sample of accelerometer data as a function of time over a 14-day study period for four study participants. The horizontal axis represents the temporal scale over 14 days, and the vertical axis shows the level (or intensity) of activity measured by the accelerometer. By comparing the activity charts from these three study participants, different activity patterns become obvious.

Figure 3: Sample activity outputs over a 14-day study period
(source: VA Study for Mobility Outcomes Pilot Study – 2004)



Combined Travel and Physical Activity Measurement Methods

GeoStats is presently involved in several physical activity studies that are deploying wearable GPS devices in tandem with activity monitors (i.e., accelerometers) to collect travel and physical activity data simultaneously from study participants. The Veterans Affairs Study for Mobility Outcomes (VA Mobility Study) and the Fresno Asthmatic Children's Environment Study (FACES) are two of these studies. These studies are focused on two very diverse and distinct population groups – visually impaired veterans (typically elderly retired military personnel) and children with asthma. Table 2 lists the basic attributes of each of these two ongoing physical activity studies.

Table 2: Summary information on several recent physical activity studies

	VA Mobility Study	**FACES**
Length	3.3 years	2 years
Timeline	09/05 through 12/08	07/06 through 06/08
Type	Before/After	School/Summer
Deployment Period	14 days per phase	5 days per phase
Age	Average age 72; range from 47-90	Ages 7-18
Size	200 participants 400 deployments	150 participants 87 deployed twice 7 deployed thrice

The goal of the three-year VA Mobility Study is to assess change in the amount, frequency and patterns of mobility associated with orientation and mobility (O&M) training provided in the course of blind rehabilitation sponsored by the Department of Veterans Affairs (VA) by using a combination of GPS, GIS, and accelerometer technologies. This study will demonstrate the capability and efficacy of these technologies as an effective, low-cost and highly objective mechanism to collect mobility outcomes of veterans who receive blind rehabilitation training. This study is sponsored and led by the VA with support from GeoStats LP.

FACES, which first began in 2000, is a large epidemiological study of the effects of air pollution on children with asthma. This study is sponsored by the National Institutes of Health and is led by the University of California, Berkeley, with support from Sonoma Technologies, Inc, and GeoStats LP. About 300 children who reside in the Fresno, California area have been enrolled in the study. The overall study goal is to determine the effects of different components of particulate matter (PM), in combination with other ambient air pollutants, on the natural history of asthma in young children. In 2006, FACES added a GPS and accelerometer component to the study; 150 children were eventually instrumented. The physical activity data will be evaluated in conjunction with pollution sensors that have been installed at the children's home and school locations to assess the amount of time and levels of physical activity experienced by the study subjects while indoors and outdoors at these locations.

Instrumentation

In each of these studies participants were provided with a wearable GlobalSat GPS Data Logger and an ActiLife ActiGraph accelerometer, and asked to wear both pieces of equipment for the duration of their assigned study period. The participants were required to wear the GPS clipped to their waist or to a backpack/purse, and carry the device anytime they travelled outdoors. Participants were asked to wear the ActiGraph clipped to their waist during all waking hours, unless they were swimming or bathing.

Processing Methodology

In each study, GeoStats provided wearable GPS data loggers and was responsible for processing both GPS and ActiGraph activity monitor data collected by study participants. To do this, GeoStats loaded the two datasets into a single database that was linked based on the date and time stamp available in each record. GPS data were recorded on a second-by-second basis while physical activity data typically consists of activity counts collected in one-minute epochs. Consequently, the one minute activity value collected by the activity monitor was assigned to each GPS point in the corresponding minute of activity. Different activity levels (inactive, light, moderate, and vigorous) were assigned for each minute of activity based on the appropriate activity level thresholds for each study population group. Minutes of activity falling into the inactive or moderate/vigorous categories were then aggregated into bouts of activity.

Once the data merge and activity-level-assignment steps were complete, GeoStats' Trip Identification and Analysis System (TIAS) was used to process the collected data into trips. TIAS enables data analysts to reenact GPS trips within a GIS framework while simultaneously viewing associated speed and activity graphs. Trip ends were confirmed at the activity change time points based on stop times and other characteristics of the GPS and activity data within the GIS framework supported by TIAS. Travel modes were also assigned for each activity segment using the TIAS mode assignment module and were stored in the database.

After all data processing was complete, complete datasets were delivered to the research team for further analysis and interpretation. The research team could also access processed data via password-protected project websites that provided participant status information and travel details, and the visualization of individual trip and activity data made available by means of maps and charts shown on a trip by trip basis.

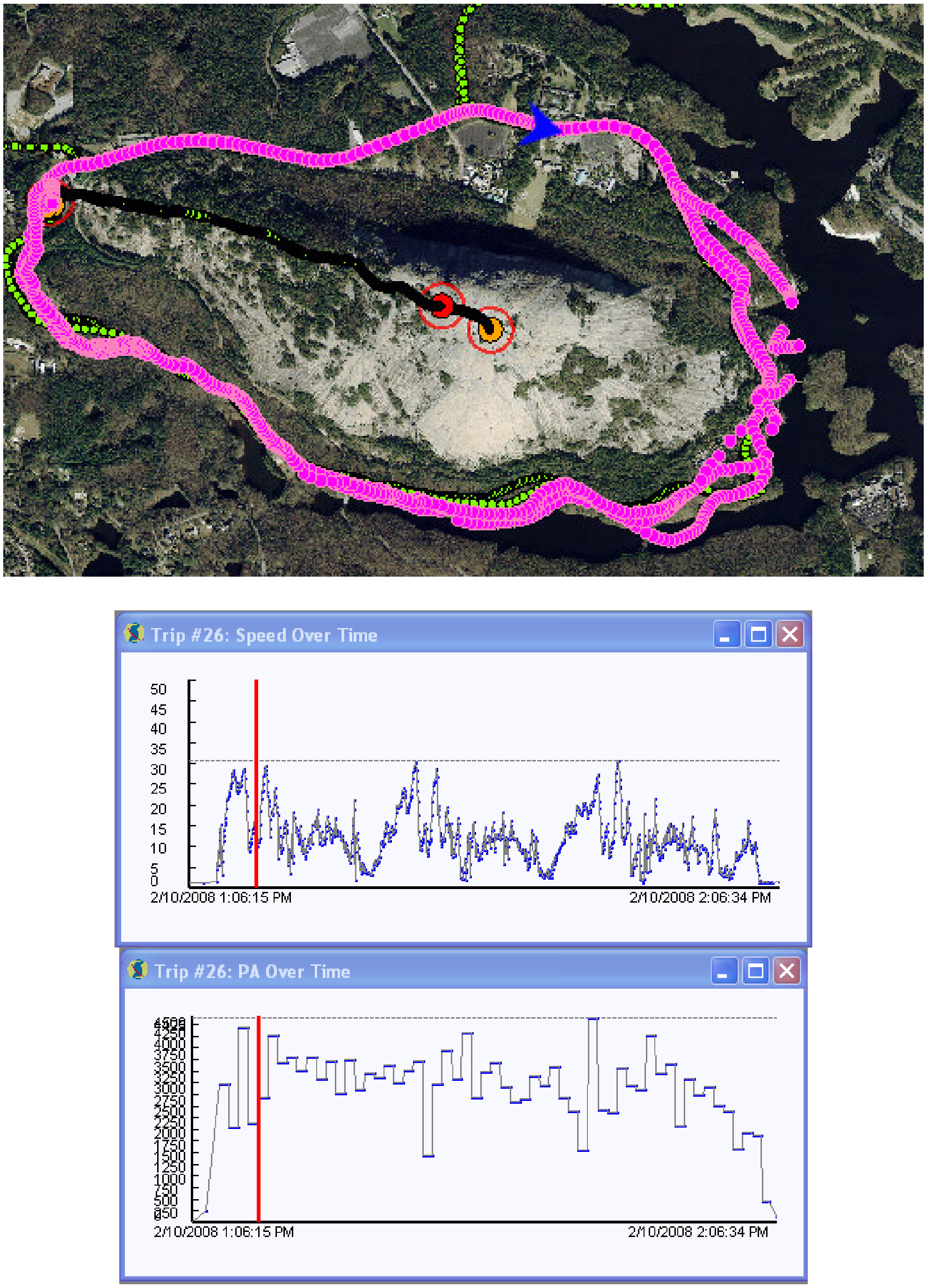
Data Display and Sharing

Scientific visualization has been described in the past as the process of producing and examining images of data with the goal of increasing human comprehension (Hearnshaw and Unwin, 1994). It is based on the idea that humans are able to reason, analyze, and learn more productively in a visual setting (Gahegan, 2000). Gahegan also points out the inherent quality of visual data that allows for the exploration of structure and pattern within multi-dimensional data. Given the large number of attributes that are associated with human activity, visualization provides a means of exploring and analyzing such complex datasets (Kwan, 2003). Dimensionality in the visualization of physical activity is advanced by the introduction of simultaneous GPS data collection. Geographic visualization, or distinct visual representations that lead to the visibility of spatially- and contextually-based questions, is made possible through the use of GPS. This added dimension facilitates the detection and analysis of spatial patterns and relationships in the geographical context of a study (Kwan, 2000).

In order to generate tables, graphics and maps for this paper, GeoStats asked several employees to carry a wearable GPS and accelerometer for a five-day period during their regular daily routine. The collected data were then processed using the same methodology described in the previous section. GeoStats' internal testing website, similar to those used by GeoStats' clients during studies, was used to display data. This section shows examples of ways to visualize GPS and accelerometer data to increase the understanding of travel behavior and physical activity.

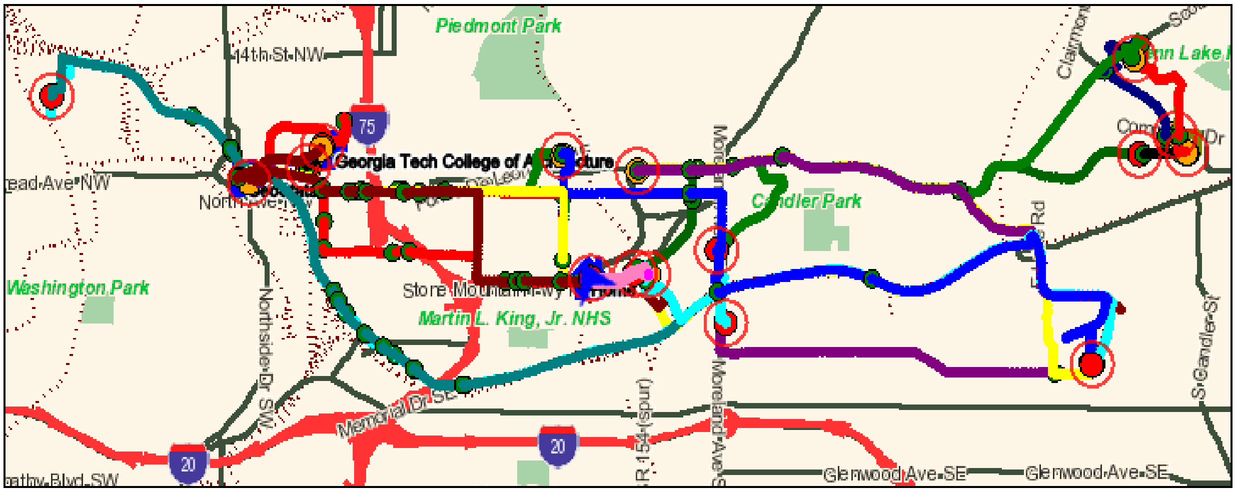
GeoStats uses a combination of Geographic Information Systems (GIS), GPS data, and physical activity graphs to paint a more complete picture of overall physical activity. Figure 4 shows a bicycle trip (three loops) around Stone Mountain Park in Atlanta, GA with associated speed and activity graphs. The location of the blue arrowhead on the screen corresponds with the point in time (represented by the vertical red line) on the speed and activity graphs.

Figure 4: GPS trace of bicycle trip with speed and activity graphs



The ability to visualize all trips made over a multi-day deployment period can increase the understanding of physical activity in space. Figures 5 illustrates trips made during a five day deployment period on a single map, color coded by trip.

Figure 5: All trips during deployment period, color coded by trip



A multi-modal trip from home to school is shown in Figures 6 & 7. This person drove from home to their place of employment, parked their vehicle and walked to school. Figure 6 shows the GPS trace for this trip, color coded by speed. Figure 7 shows the same trip, but color coded by physical activity level.

Figure 6: Multi-modal trip, color coded by speed

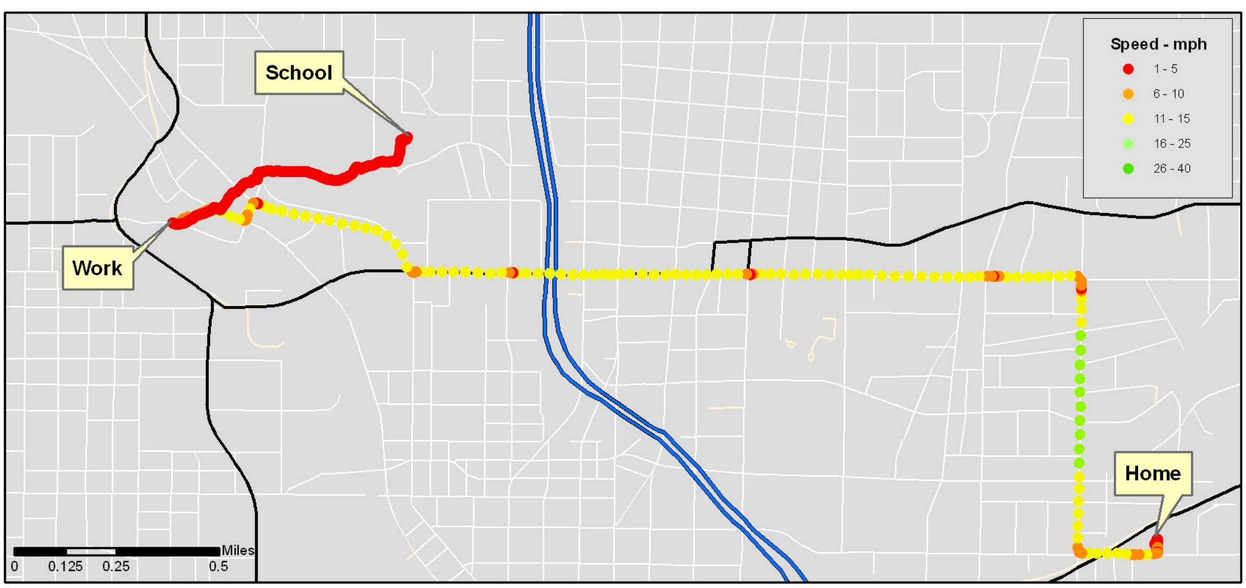
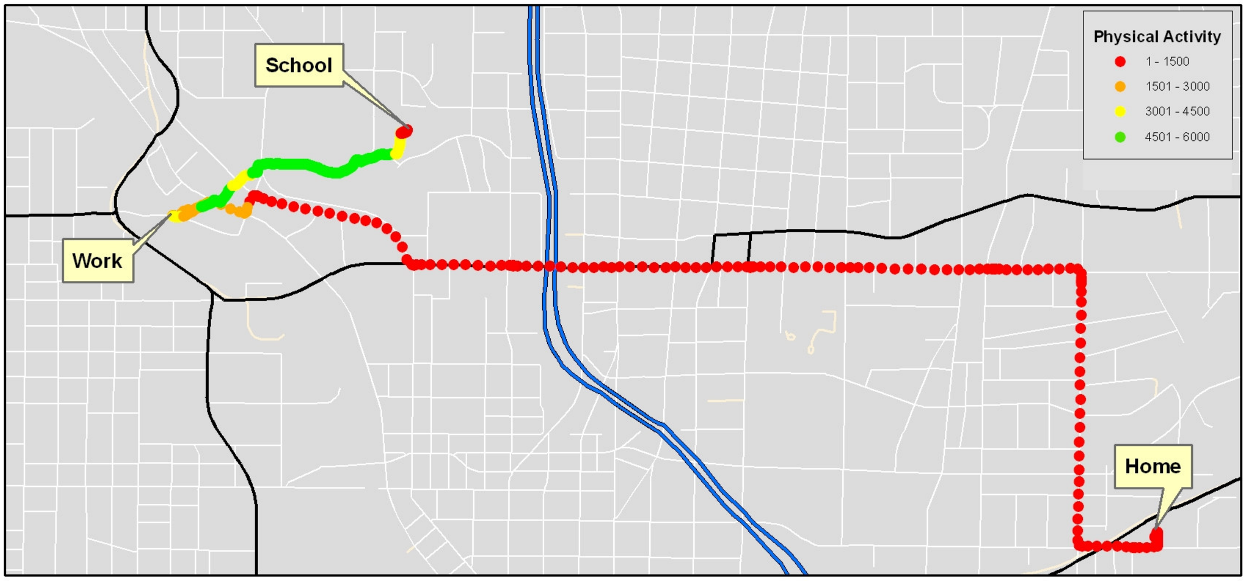
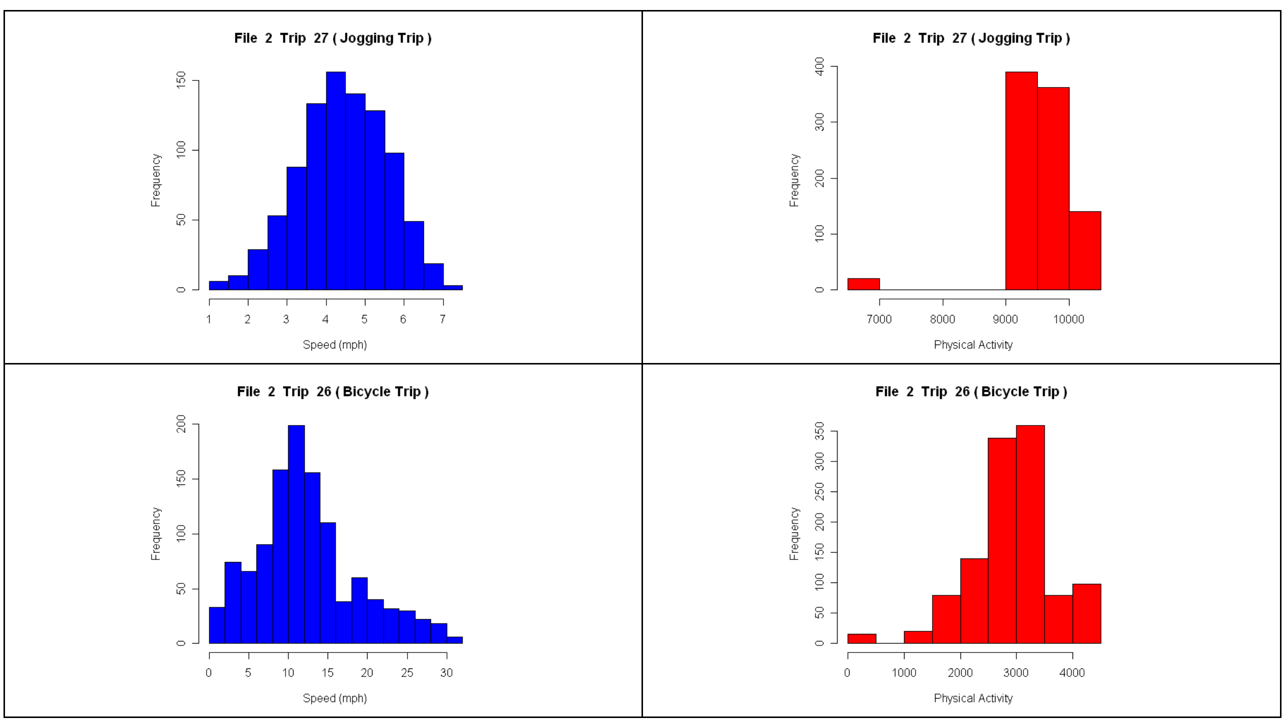


Figure 7: Multi-modal trip, color coded by intensity of physical activity



Another way to visualize GPS speed and physical activity data is through the use of histograms; these plots tend to show the variability of these data better than the time sequential plots shown in Figure 4. Figure 8 shows a set of these plots for two non-motorized trips.

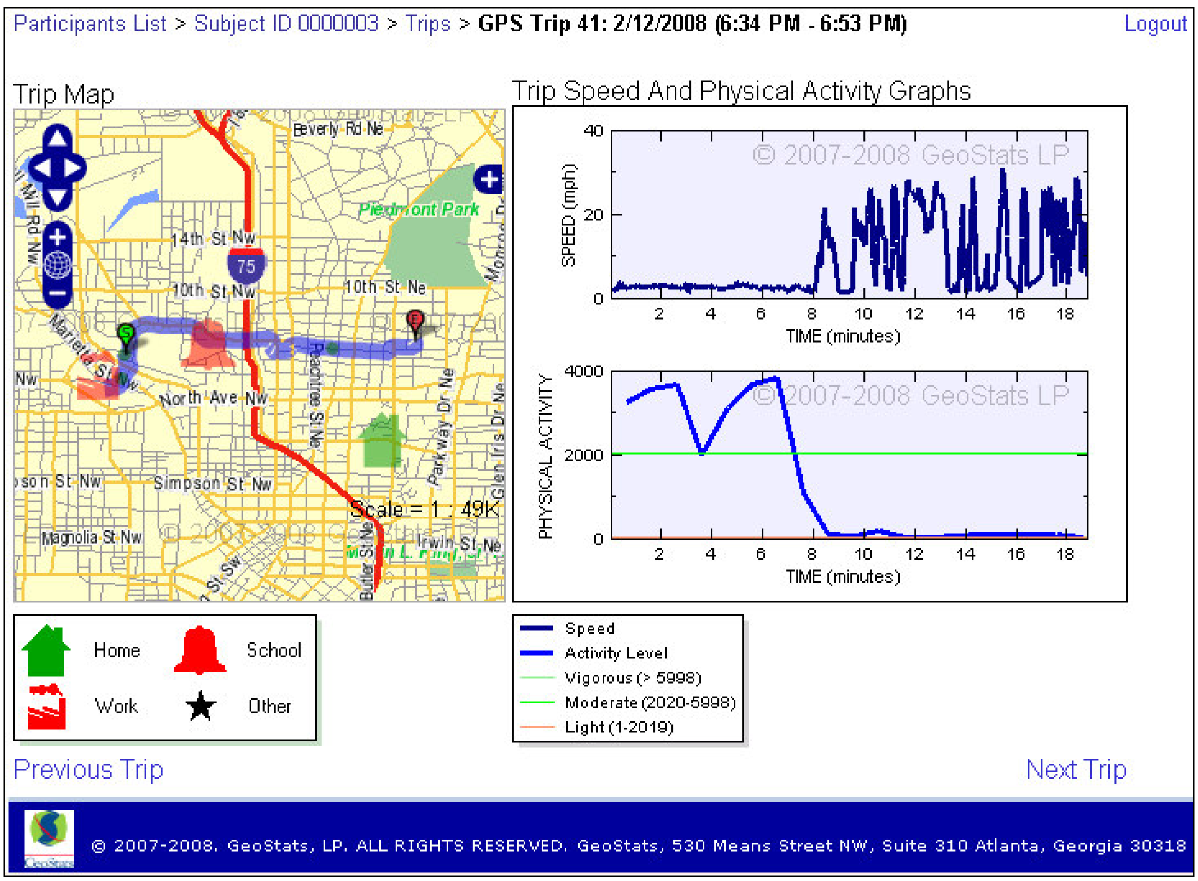
Figure 8: Speed and physical activity histograms



The map trace of each trip measured by the GPS device is made available on the project website, along with the speed and activity graphs for that trip. The map also displays icons at all habitual destination locations, which include home, work, and school locations reported for the study participant during the recruitment process.

Figure 9 shows a screen from the internal GeoStats Physical Activity Study website. In this screen, one can see the trace of a trip that consists of an initial walk to a vehicle (as confirmed by the low speed and high activity levels seen at the start in the graphs to the right) followed by a car trip made on a major arterial road in Atlanta (as detected by the stop-and-go speed profile combined with the low activity levels in the same graphs).

Figure 9: Individual trip summary map and graphs available on website



A series of summary tables and reports are also available on the website including a trip table (Figure 10) and a daily summary table (Figure 11). The trip table includes useful statistics such as trip start and end time, duration, distance, average and maximum speed. The daily summary report gives aggregate statistics on trips and physical activity levels by deployment day.

Figure 10: GPS trip summary table

GeoStats LP **DemoPAStudy**

Participants List | Deliverable List

Participants List > Subject ID 0000003 > **Trips** Logout

Travel Day: 2/12/2008

Trip	Travel Day	Travel Day Trip	Date	Start Time	End Time	Duration (minutes)	Distance (miles)	Avg Speed (mph)	Max Speed (mph)	Trip Details
37	5	1	2/12/08	8:02:23 AM	8:15:43 AM	13.3	2.5	11.3	39.5	Go
38	5	2	2/12/08	2:41:04 PM	2:57:04 PM	16.0	0.7	2.5	3.7	Go
39	5	3	2/12/08	4:26:34 PM	4:43:18 PM	16.7	0.7	2.6	3.5	Go
40	5	4	2/12/08	4:46:52 PM	4:54:12 PM	7.3	0.3	2.5	3.1	Go
41	5	5	2/12/08	6:34:24 PM	6:53:11 PM	18.8	2.6	8.2	30.9	Go
42	5	6	2/12/08	6:54:29 PM	7:07:46 PM	13.3	3.0	13.5	45.9	Go
43	5	7	2/12/08	7:33:13 PM	7:42:18 PM	9.1	3.6	23.6	43.1	Go

Figure 11: GPS daily report available on website.

GeoStats LP **DemoPAStudy**

Participants List | Deliverable List

Participants List > Subject ID 0000003 > Reports > **Daily Report** Logout

Daily Report for 0000003

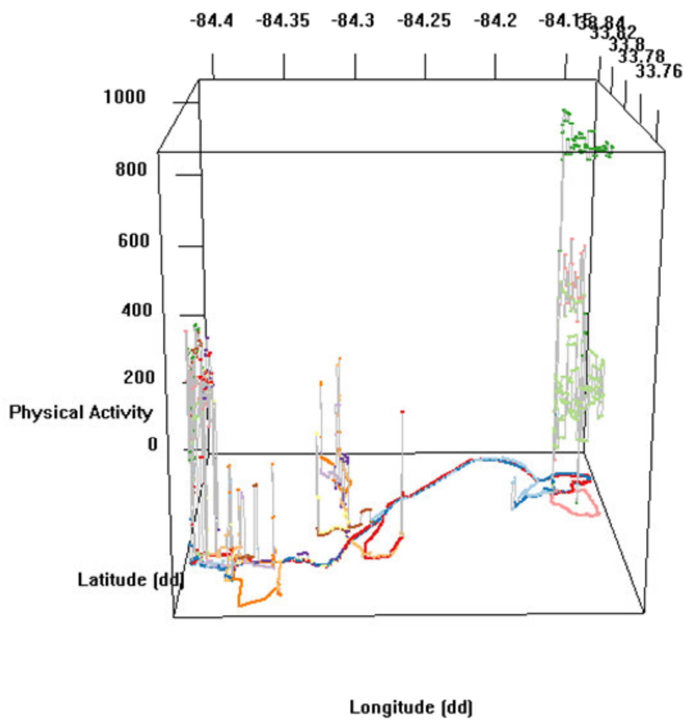
Travel Day	Day	Trips	Duration (minutes)	Distance (miles)	Actigraph Worn (min)	Inactive (%)	Light (%)	Moderate (%)	Vigorous (%)
1	2/08/08	8	71.5	8.6	211.0	18.0	58.8	22.7	0.5
2	2/09/08	16	220.7	67.7	538.0	13.0	72.7	12.3	2.0
3	2/10/08	7	200.9	65.1	602.0	17.4	63.6	11.3	7.6
4	2/11/08	5	67.5	5.5	529.0	18.1	60.3	17.0	4.5
5	2/12/08	7	94.5	13.3	496.0	13.7	72.4	13.9	0.0

Other Visualization Methods for Exploring Travel and Physical Activity Data

GeoStats also investigated the use of the third dimension as an aid for the visualization of travel and physical activity data. Previous work done by Kwan (2000 and 2003) and Rinner (2004) focused on using the third dimension to symbolize time, the authors examine here the use of speed and physical activity values as height for the GPS points.

The tools used in exercise were Google Earth, which is available for non-commercial use from http:// earth.google.com/, and the rgl package (Adler and Murdoch, 2008) in R, an Open Source Statistical package (R Development Core Team, 2008). The rgl package uses OpenGL to display data in 3D, using its basic capabilities the plot of physical activity in Figure 12 was created, the plot clearly identifies areas of higher physical activity. However, the absence of geographical context makes it harder to interpret. R does have the capability to plot GIS data; however the authors were not able to use it together with the 3D plotting capabilities.

Figure 12: GPS traces with height based on physical activity.



To explore the use of Google Earth, GeoStats developed a translator that creates KML files from TIAS' relational database. This translator created individual trip line features by combining each trip's GPS points in sequence, and trips were assigned colors from a fixed palette.

To explore the 3D capabilities of Google Earth this translator was build with the capability of using either speed of physical activity values as height for the GPS points. Figures 13 and 14 show the same set of color-coded GPS trips (circling Stone Mountain Park in Atlanta, GA), but with different sources of height information.

Figure 13: GPS traces with height based on physical activity, height (m) = PA (counts) / 10

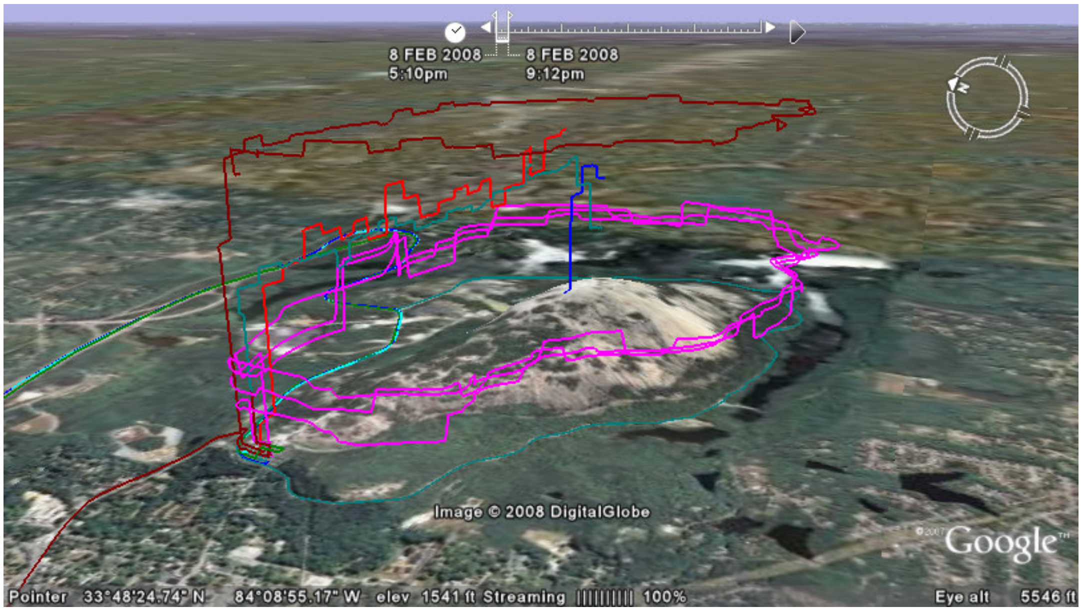
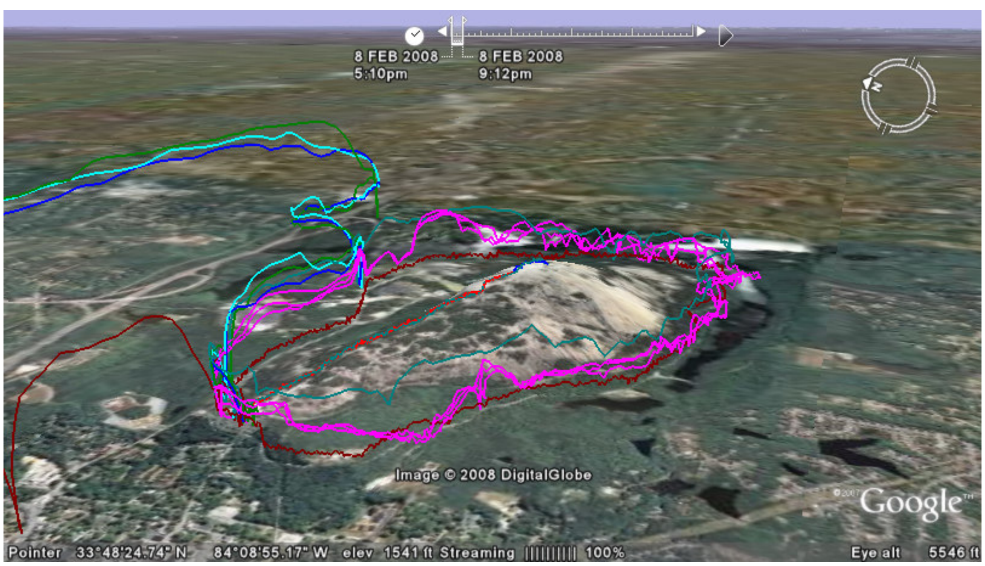


Figure 14: GPS traces with height based on speed , height (m) = speed (mph) * 10



Comparing the two sets of traces it can be visualized which ones are motorized and which ones are not. Motorized trips feature higher speed values with low physical activity counts (lines appear clamped to the ground), they can be seen leading to and from the Park site. Similarly, it is also possible to identify different non-motorized modes based on the levels of physical activity and speed as depicted.

Summary

The use of in-vehicle GPS in household travel surveys and accelerometers in physical activity studies has become commonplace over the last decade. Recent advancements in GPS receiver and battery technology have generated a range of reasonably priced wearable GPS data loggers that can be deployed to persons in both types of studies without increasing respondent burden. The prevalence of both GPS and accelerometer technologies and their combined use has increased the need for advanced visualization methods.

For many years, physical activity data were collected using subjective means (primarily self-report diaries). The advent of pedometers, and most recently accelerometers, has allowed researchers to objectively collect physical activity data. Data collected using these technologies have traditionally been analyzed and presented without a geographic component using summary tables and graphs. The recent introduction of wearable GPS devices into physical activity studies has added a spatial component to these data. This added component has vastly expanded the data visualization options, including the capability to display GPS traces on maps according to physical activity and speed.

These same recent technological advances have allowed more extensive use of wearable GPS in person-based household travel surveys. This results in a more complete picture of household travel through the capture of non-motorized and multi-modal trips. GIS based software and data layers routinely aid in the interpretation of data and assist in the identification of transportation modes, specifically in urban areas with complex public transportation systems.

The rapid evolution of GPS and GIS technologies have and continue to open up an exciting range of analysis possibilities in the fields of travel surveys and physical activity studies. Advanced visualization techniques enable researchers to discover data patterns that may be difficult or impossible to detect through ordinary means. The ability to visualize GPS and physical activity data independently and in concert allows a broader audience to better understand these complex data and their interactions.

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