Using high resolution transit geolocation data to analyze performance and identify intersections that contribute to transit delay

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Introduction

As cities are faced with growing congestion, the improvement of mass transit presents a clear option for improving transportation system performance. However, scarce funding for large-scale investments has focused attention toward the improvement of surface transit, which suffers equally from roadway congestion absent the deployment of transit priority treatments. In order to maintain the reliability of surface transit service, cities and transit agencies have sought to deploy such treatments, examples of which include transit-only lanes, queue jumps, and transit signal priority (TSP). However, in order to do so effectively they must determine where transit vehicles are facing the greatest delay. Additionally, after these treatments are deployed there is a need for an analysis with a high enough resolution to capture the improvements' effects. As agencies introduce tactical transit priority improvements at a small spatial scale, there is a realization that intersection level transit analysis is lacking.

In this paper, we present two methodologies by which transit delay attributable to signalized intersections can be assessed using high resolution GPS data. The first methodology quantifies delay as transit vehicles travel through an intersection, and the second methodology identifies the fraction of transit vehicles stopping as they approach a signalized intersection. Together or separately, these methods can help transit agencies and/or highway departments prioritize installation of TSP, the re-timing of signals, or other transit priority treatments. The data for this study was collected in San Francisco using transit vehicles in the San Francisco Municipal Transportation Agency (SFMTA, Muni) fleet. While the data used in this study was derived from a TSP request system, newer generations of automated vehicle location (AVL) technology have also attained a similar data resolution and therefore could also be used as inputs to these methods.

Background

Recent work has evaluated a variety of methodologies for measuring transit delay at the route and segment level as well as the potential to use these measurements to approximate overall vehicle delay. The advent of widespread AVL and automated passenger counter (APC) data has greatly reduced the need for manual observation of transit performance at the route and segment level. Much of the literature in this area is focused on the analysis of line or segment performance and the improvement of real time customer information. Van Oort et al. discuss the potential of widespread AVL data to provide customers with improved information such as the likelihood of transfer success and planners with the ability to better schedule and coordinate operations as well as identify bottlenecks [1]. Hu & Shalaby used AVL information to assess the effect of route and segment characteristics, such as intersection density, pedestrian activity, signal cycle lengths, and the provision of TSP, on a variety of reliability measures[2]. Wong & Khani used APC data in place of AVL data to examine vehicle dwells at timepoints and subsequently estimate dwell times and traffic delay[3].

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[1] van Oort et al., "Data Driven Improvements in Public Transport."
[2] Hu and Shalaby, "Use of Automated Vehicle Location Data for Route- and Segment-Level Analyses of Bus Route Reliability and Speed."
[3] Wong and Khani, "Transit Delay Estimation Using Stop-Level Automated Passenger Count Data."

In terms of specifically examining signal delay, Hellinga et al. found that an APC/AVL system that specifically records vehicle starts and stops was able to replicate manual measurements of signal delay with a high degree of accuracy[4]. Citing the high IT requirements of high-resolution data, Zhang et al. sought to model signal delay using a low resolution AVL source, finding that it could approximate observed measurements for delay when averaged over a half-hour period. However, distributional data was not examined and the case study intersection had no transit stops within a 200-meter radius[5]. In a non-transit application, Remias et al. used anonymized trajectory data collected from private vehicles to evaluate signal timing patterns on an uncongested arterial[6].

However, while these sources can provide aggregate performance measures, they frequently lack the resolution needed to analyze the cause of delays. The lack of resolution found in traditional AVL and APC sources frequently prevents the measurement of delays at the intersection level, as records are generated every 20-30 seconds or only at "events" such as when the bus starts and stops. Newer AVL systems may alleviate this issue, with resolutions as high as one record every five seconds or even one record per second. Recent studies with five-second resolution transit AVL data have examined its utility for measuring arterial speeds[7], congestion hot spots[8], and time saved from transit route changes[9]. Coghlan et al. used one record per second AVL data (the same resolution used in this paper) to classify transit delays and improve real-time customer information. To isolate signal delay, an 80-foot buffer surrounding a point-based map of signals was used in conjunction with a binary test of whether the bus doors were open or closed (to avoid capturing stop dwells adjacent to intersections)[10]. Building on this prior work, the methodologies discussed below seek to leverage high-resolution data to investigate the impact of signalized intersections on transit delay and identify locations where transit priority improvements can be tactically deployed.

Data collection process

The data for this study consists of three main components: 1) location data from transit vehicles, 2) manually-determined analysis regions adjacent to signalized intersections, and 3) General Transit Feed Specification (GTFS) schedule data that incorporates route and trip information. The location data is collected through a GPS-based transit signal priority request system that has been installed on most SFMTA buses, in which transit vehicles transmit their position at a rate of one record per second to wayside GPS detectors that are connected to traffic signal hardware. The wayside hardware searches for transit vehicles within designated approach zones and places a signal priority request if a vehicle is detected. The on-board hardware stores a record of its locations, along with the speed, vehicle ID, trip ID, and route ID, and uploads this information over WiFi when vehicles are returned to yards. As more vehicles are equipped with the current generation of TSP equipment, a richer set of data can provide citywide insights and allow further

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[4] Hellinga, Yang, and Hart-Bishop, "Estimating Signalized Intersection Delays to Transit Vehicles."
[5] Zhang et al., "Estimating Control Delays at Signalised Intersections Using Low-Resolution Transit Bus-Based Global Positioning System Data."
[6] Remias et al., "Evaluating the Performance of Coordinated Signal Timing."
[7] Figliozzi and Stoll, "A Study of Bus High-Resolution GPS Speed Data Accuracy."
[8] Stoll, Glick, and Figliozzi, "Using High-Resolution Bus GPS Data to Visualize and Identify Congestion Hot Spots in Urban Arterials."
[9] Glick and Figliozzi, "Evaluation of Route Changes Utilizing High-Resolution GPS Bus Transit Data."
[10] Coghlan et al., "Assigning Bus Delay and Predicting Travel Times Using Automated Vehicle Location Data."

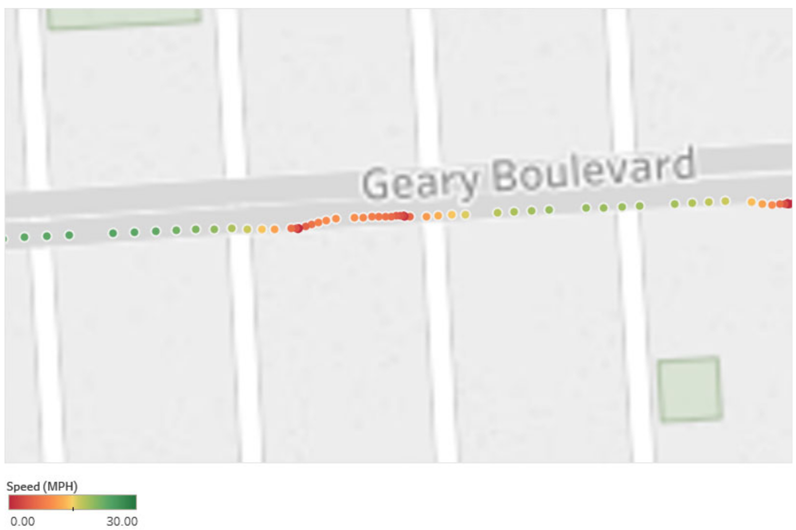
disaggregation to look at specific lines at limited hours. However, as shown in Figure 1, the even without full fleet penetration a full day of data can provide a 2.7 million-point snapshot of transit service across San Francisco.

Figure 1: Visualization of one day of high-resolution GPS data (2.7 million points) acquired from SFMTA buses, with each point colored by vehicle speed.

In order to focus on specific regions, in this case the approaches to signalized intersections, two types of input data were used to identify areas of analysis. For the measurement of delay, each approach to an intersection served by transit is identified with a "check-in" and "check-out" location. While the check-out location was almost always located at the far-side crosswalk of the intersection (but upstream of any far-side bus stops), the location of the "check-in" coordinate varied by location. The coordinate was located following a general principle of being far enough from the intersection to capture queueing delay but near enough that other delay sources such as crosswalks, other signalized or stop-controlled intersections, or bus stops would not be captured. Typical locations included the middle of the block preceding the signal (for longer blocks) and immediately downstream of the preceding delay source (for shorter blocks). For the measurement of vehicles stopped on approach to the signal, a bounding-box approach was used. Following a similar logic to the check-in point for delay measurements, the bounding box was extended approximately 300' along the path of travel upstream of the intersection or to the nearest preceding roadway feature that could cause the vehicle to stop regularly (crosswalks, controlled intersections, and bus stops).

Analysis

Data analysis was primarily conducted in Python for each of the two metrics (delay and percent stopped on approach). The first step in both analyses was to group the location data into unique transit trips. For each intersection this was done by looking at unique date-trip ID combinations, as there is only one instance of any trip ID that operates on a given operational day. GTFS schedule data was then joined to the trip ID in order to isolate inbound or outbound trips. Route identifiers are already included in the location data, which enabled analysis of individual routes on roadway segments that host multiple transit lines. For a given intersection, the analysis then proceeded on a basis of unique trips (as defined above) on a given line and direction.



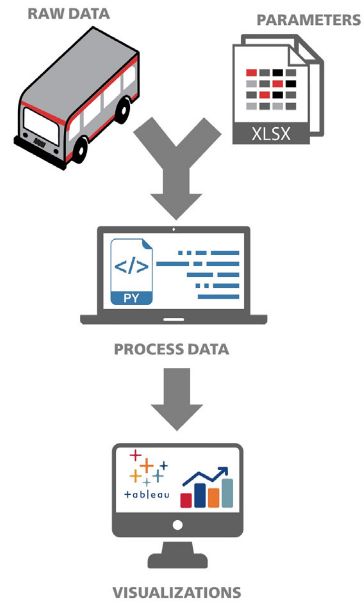


Figure 2a (left): Illustration of location data for a single trip approaching a far-side bus stop at Geary Boulevard & 9th Avenue and subsequently stopping at the following signalized intersection.
Figure 2b (right): Data acquisition and analysis process.

The delay analysis began by setting a search area around the check-in and check-out points. The script then took the location points nearest the input coordinates and determined the travel time between the points. This was compared with a travel time corresponding to the posted speed limit to determine delay. The output file can be generated for multiple routes at one time and provides a list of delay records for unique trips at a given intersection. The analysis of vehicles stopped on approach to an intersection began by examining all points within the bounding box regions defined for each intersection. For a unique trip at a given intersection, all points with a travel speed below two miles per hour were classified as a stop. The script then compared the number of unique trips that stopped within the approach zone to the total unique trips to calculate the percent of transit vehicles stopping on approach to the intersection. Once the data was processed, the flat files were pushed to a Tableau server where they are available for dashboard consumption.

Results

In order to visualize the results effectively and provide a snapshot of system performance, dashboards were created in Tableau. The Python outputs, which associate each intersection with a series of either delay values or true/false conditions for whether a transit vehicle stopped on approach, were mapped geographically with color codes based on the median delay or percent stopped. This allowed quick identification of intersections that are causing the most delay to transit vehicles.

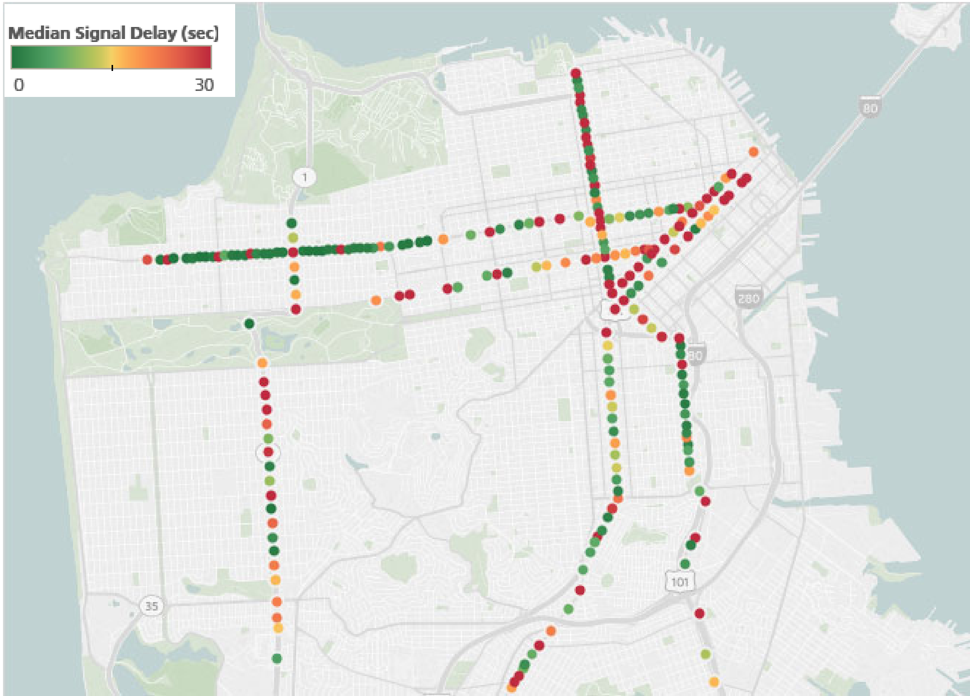


Figure 3: Visualization of median signal delay across a subset of the SFMTA system focused primarily on Rapid and frequent corridors.

In addition to the map, tables were also generated to show aggregated values for the sampling period. Table 1 and Table 2 show percent stopped and median delay values for a subset of the intersections shown in Figure 2. Note that while several months of data collection were required to reach the record counts shown in the tables, these values are only for AM peak vehicles on the rapid half of a local/rapid bus pairing. If collection is expanded to include the full day or the local route that shares the corridor, record counts allowing for robust statistical analysis can be achieved in a much shorter time span.

Table 1: Percent of northbound 14R-Mission Rapid vehicles stopped on approach at intersections on Mission Street in San Francisco during the AM peak (6-9AM); November 2018-March 2019

Intersection Name	% Stopped	Number of Records
25th St & Mission	29%	400
24th St & Mission	47%	408
23rd St & Mission	41%	415
22nd St & Mission	69%	379
21st St & Mission	5%	374
20th St & Mission	14%	378
19th St & Mission	55%	396
18th St & Mission	70%	394
17th St & Mission	4%	377
16th St & Mission	33%	375
15th St & Mission	34%	380
14th St & Mission	59%	362

Table 2: Median delay of northbound 14R-Mission Rapid vehicles at intersections on Mission Street in San Francisco during the AM peak (6-9AM); November 2018-March 2019

Intersection Name	Median Delay (sec)	Number of Records
25th St & Mission	4	372
24th St & Mission	14	380
23rd St & Mission	11	367
22nd St & Mission	19	365
21st St & Mission	2	350
20th St & Mission	3	347
19th St & Mission	16	343
18th St & Mission	20	346
17th St & Mission	2	343
16th St & Mission	3	339
15th St & Mission	7	329
14th St & Mission	17	332

Histograms of intersection delay were also created to show how delays are distributed. Many intersections show a somewhat bimodal behavior – one peak close to zero represents vehicles that cross the intersection during the green phase while another peak represents vehicles arriving on red. Figure 3 illustrates this behavior for an intersection with a sixty-second cycle length, with an initial peak at near-zero delay and a broader peak at approximately 45 seconds of delay.

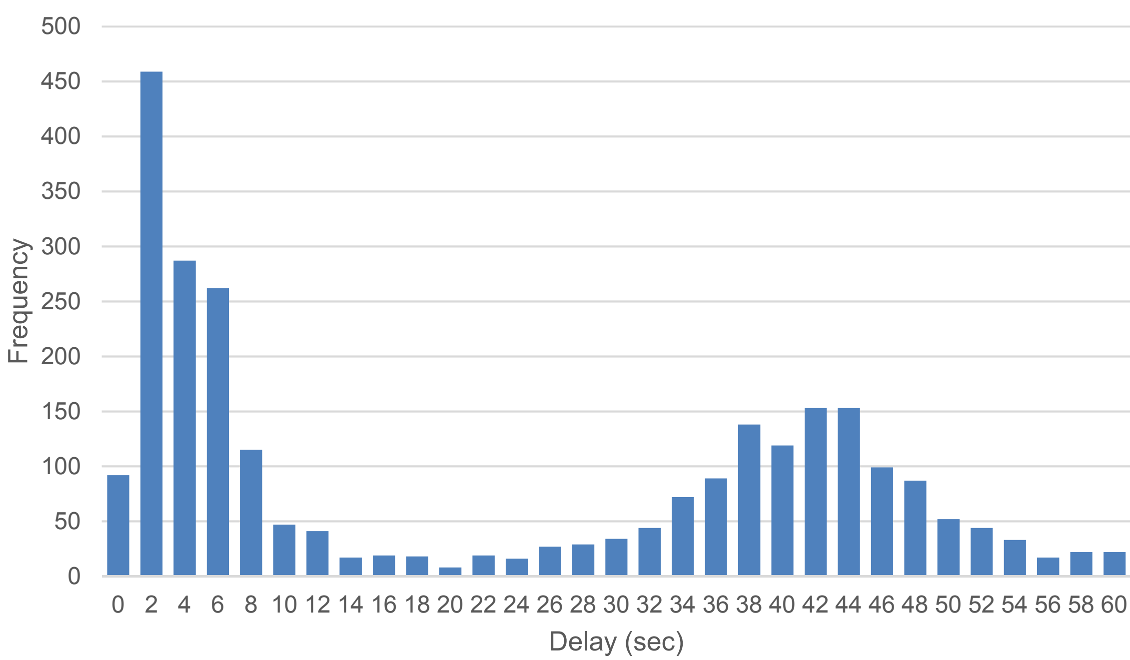


Figure 4: Distribution of signal delay for northbound buses on the 14R-Mission Rapid line at the intersection of 16th Street & Mission Street.

All dashboards have been developed with the ability to select specific date ranges which will allow for future before/after studies. The current dashboards have begun to be used by engineers and signal shop electricians in order to identify intersections with potential issues for troubleshooting. Additionally, engineers have identified high performing intersections in order to understand what features from these installations could be replicated in other locations. A plan for a large-scale TSP on/off study is underway in San Francisco and this methodology will lay the foundation for systemwide intersection level analysis.

Future Work

As with many techniques for classifying transit delay sources, these measures still face challenges in the case of transit stops on the near-sides of intersections. Many bus and light rail stops in San Francisco and other cities are located with minimal distance between the stop location and the stop bar of an adjacent intersection. This makes it difficult to separate transit stop activity from delay attributable to the signal, particularly when using the percent stopped on approach method. It may be possible to extract delay and stops on approach that are solely attributable to signal state if data on the vehicle doors can be obtained from APC data. APCs typically register when vehicle doors are open, which would allow this dwell distribution to be subtracted from a combined delay distribution or examination of instances where the vehicle stopped on approach but did not open its doors. However, the decomposition of the combined delay distribution could be complicated by the practice of vehicles dwelling with their doors open (or reopening doors for passengers arriving while the vehicle is stopped) until receiving a favorable signal. Lastly, GPS-based systems have been shown to face challenges establishing precise locations in urban canyons. The GPS drift observed in areas with large numbers of high-rise buildings and by stopped vehicles pose challenges to the use of this data in disaggregate form.

The use of GPS data at such high resolutions has been previously identified as a technological challenge – primarily regarding data storage, but also in terms of data transmission limitations through AVL systems. As a result, further investigation is warranted in order to determine if similar findings could be achieved with a lower resolution of points. This could also enable this methodology to be applied using data from a wider variety of sources and reduce the demand for data storage. Other improvements include further differentiation of nearside stops, potentially by combining the location data with other sources such as APC data that may reflect when the vehicle's doors were open. Other data integration strategies include the use of signal controller data to correlate vehicle activity with signal states. This could improve understanding of the relationship between signal activity and vehicle delay as well as providing a method of directly analyzing TSP system activity to seek out areas for improvement.

Additional future work will include before and after studies to evaluate the success of TSP and other transit priority treatments. Currently, this methodology has only been applied to San Francisco's rubber-tired transit fleet due to its use of a wireless, GPS-based TSP request system. Extension of this methodology to the SFMTA's light rail system (Muni Metro) is a desired extension of the work, but will require the identification of a data source with sufficient resolution.

Conclusion

This paper documents a process by which high-resolution transit vehicle location data can be used to assess transit delays at signalized intersections and help transportation agencies prioritize areas for investment in signal re-timings, signal priority, or other treatments to reduce transit delay. Transit agencies with an existing deployment of a high-resolution AVL or TSP system can directly apply this methodology to either prioritize new transit-preferential treatments or to evaluate the effectiveness of such treatments after they have been installed. Even if high-resolution location data is not available fleet-wide, similar results can likely be achieved by lengthening the sampling timeframe and ensuring equipped vehicles are distributed to routes of interest. There is still work to be done in order to make this methodology more robust among all intersections and vehicle modes. As AVL systems evolve and become capable of higher-resolution data, it is predicted that this methodology will become more widely accessible.

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