Journal Title
XX(X):1–10

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DOI: 10.1177/ToBeAssigned
www.sagepub.com/
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Multi-Scale and Multi-Variate Transportation System Visualization for Shopping District Traffic and Regional Traffic

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Abstract

In this paper, we present a suite of visualization techniques for sensor-based transportation system data at different scales to facilitate the exploration of interconnected traffic dynamics at intersections and highways. These techniques are designed for analyzing multivariate traffic data from radar-based highway sensors and camera-based intersection sensors recording turn movements and vehicles speed, in the Chattanooga Metropolitan Area, with the capability of (a) revealing multi-scale mobility patterns using different levels of data aggregation (e.g., individual sensor for microscale, multiple sensors along a corridor for mesoscale, and a larger number of sensors across the region for macroscale visualization) at different intervals (e.g, 5-minute intervals, time of day, full day, and day-of-the-week, etc), and (b) exploring the spatial variation of multiple traffic-related variables (e.g. volumes, speeds, turn movements, and traffic light colors) provided by the sensors. We close with a case study to demonstrate the effectiveness of our multiscale and multivariate visualization techniques: At microscale, we focus on intersection data from a shopping district around Shallowford Road in East Chattanooga. For mesoscale visualization, we study the Shallowford Road corridor and an adjacent stretch of I-75. At macroscale, we include highway data from the entire Chattanooga Metropolitan Area. All visualizations are integrated into a web-based situational awareness tool to promote user access and interaction. At a minimum, each visualization provides the option for selecting dates for real-time (depending on sensor availability) and historical data, and additional information on hovering, though most provide much more detailed information, including different views of the selected data, or interactive highlights.

Keywords

multiscale visualization, multivariate visualization, shopping district, corridor, intersection, traffic flow

Introduction

Performing mobility analytics at a regional scale is a complex endeavor that are associated with multiple data challenges. There is a broad range of potential big-data sources, ranging from static data (e.g., roadway networks, traffic timing plans) to real-time dynamic data (e.g., traffic volumes and speeds, traffic signal phase and timing, etc.). Available data streams often come from different systems or vendors with potentially distinct formats or inconsistent time intervals. Due to the large volumes and varying types of dynamic data, tailored data science approaches at various scales are required to obtain meaningful and comprehensive insight into the transportation system.

In this paper, we describe visualizations which are part of an interactive situational awareness tool under development at the Oak Ridge National Laboratory (ORNL). This tool provides a virtual representation (or *Digital Twin*) of the Chattanooga Metropolitan Area. This Digital Twin includes features such as a mapping tool, mobility metrics, and visualizations of static and real-time data. Combining a broad set of data sources within a single tool while providing visualizations of the data can provide traffic engineers with a much clearer picture of current and developing traffic conditions. The availability of diverse datasets in a single tool also opens the door to new types of data analytics, and researchers can effectively use the data to develop innovative approaches to traffic management and control of the transportation system. The situational awareness tool can therefore be considered a stepping stone to enable new functions and applications that will ultimately result in more optimized performance of the transportation system.

The primary objective of this work is to investigate and visualize traffic patterns at various spatial scales using multivariate traffic sensor data. The scales considered are intersection level (micro-scale), corridor (meso-scale), and

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regional (macro-scale), definitions for which are provided in corresponding sections below. We present a corridor-level mapping environment with a capability to visualize spatial data such as sensor location and roadway conditions for highways and intersections. We also provide a variety of system metrics and charts from these sensors such as daily traffic volumes, time-of-day variations, and roadway speed profiles. We further explore regional-level analysis and visualization on highway speeds, volumes, and fuel economy metrics. For the present study, we focus our analysis on a segment of interstate highway 75 (I-75) and a main arterial, Shallowford Road, in Chattanooga, Tennessee. This Shallowford Road corridor services two of the largest shopping centers in the area, as well as many hotels and restaurants. It is considered a significant bottleneck for traffic in the Chattanooga area. Primarily, we analyze two data sources for this region:

- Radar sensors along I-75 (dark blue circles in Figure 1) record traffic volumes and speeds by lane at 30-second intervals
- Traffic signal camera-based sensors at intersections (orange circles in Figure 1) capture intersection-level vehicular movements and speeds at 1-second intervals. These cameras are placed at several intersections along Shallowford Road and Gunbarrel Road.

Figure 1 provides an overview of the entire region, as well as a close-up view of the shopping district in the Shallowford Road area.

Shopping centers have become major vehicular attractions in urban areas, negatively impacting local transportation systems by increasing the amount of traffic and congestion Hasan et al. (2012); Fancello and Fadda (2002). This creates socioeconomic implications for optimizing both the transportation systems design and urban planning in the shopping center vicinity Kristoffersson et al. (2018). The traffic dynamics affected by this large number of shopping trips varies significantly in speed and volume at multiple spatial scales (e.g., intersection, corridor, and region). Therefore, it is challenging to explore this ubiquitous problem using traditional modeling-based approaches.

With the recent availability of a large amount of traffic data collected from various sources, transportation management agencies increasingly require data-driven Intelligent Transportation Systems (ITS) and solutions to handle the resulting big data. These systems utilize various interactive visualizations to address the multi-scale and multi-variate nature of transportation data Sobral et al. (2019) and improve the understanding of complex urban dynamics. In past decades, many ITS solutions have been developed to provide integrated access to multi-source data, as well as different data-processing capabilities Ma et al. (2011); Zhang et al. (2011). Many of these systems were designed to visualize and analyze transportation data at a single spatial scale at a time. There are works on intersection Yan et al. (2012); Stephanopoulos et al. (1979), corridor Bertini et al. (2005); Chen (2003); Tufte (2010), and regional Pack et al. (2005); VanDaniker (2009); Pack et al. (2009) scales. Most of these systems are developed for a specific purpose pertaining to incident detection, urban traffic management, and congestion reduction Lund and Pack (2010); Wu et al. (2007); Pack and Ivanov (2008).

In relation to the development of the data-driven ITS, traffic visualization techniques are gaining popularity in the mobility sector, which employs visual channels (e.g., easy-to-understand visual representations and pattern abstractions) to represent complex traffic deteststs Hansen and Johnson (2004); Chen et al. (2015). (Ferreira et al. 2013) design a novel model which allows users to visually query taxi trips from large volume of complex geospatial taxi trip data. They implement the model into a scalable system with provides user interaction capabilities, and generates a clutter-free visualization for large results using level-of-detail techniques to offer insights of urban mobility patterns at both macroscale (regional level) and microscale (individual vehicle trips). (Guo et al. 2011) develop visualization methods to improve the investigation and analysis of microscale traffic patterns and abnormal behaviors at intersections using trajectory data. (Kurkcu et al. 2017) present a web-based tool that can acquire, store, and process bus trajectory data for the visualization and analysis of bus dwell times and travel times. Primarily focusing on the mesoscale (corridor level), the tool allows users to build customized routes through road segment selection, compare different route scenarios, as well as identify regular and abnormal traffic flow patterns.

Currently, web-based systems that can holistically visualize and analyze the dynamics of complex, interconnecting transportation systems from macro to micro scales are still rare. Many of these visualizations are developed for a specific traffic application domain at a specific spatial scales, lacking the capability of connecting traffic patterns and dynamics at different spatial scales to provide a more comprehensive insight on urban mobility. Additionally, most traffic flow visualizations rely on trajectory data that are limited in public access and are only available for a small portion of vehicles. Visualization techniques that analyze and visualize public traffic data collected from road-side sensors, which can detect all vehicle along the road, is needed. Moreover, many of the existing systems face software engineering challenges regarding system adaptability and extendibility to integrate multiple data visualization techniques (e.g., a series of linked maps and graphs) and analytical methods (e.g., spatial statistics and machine learning) in a single web environment. Therefore, many existing systems have limited capability for exploring large-scale multivariate geospatial data Anselin (2000); Bertolotto et al. (2007) or extending the system coverage to new regions.

Overview and Data

The goals of the research presented in this paper are to (1) provide situational awareness of the transportation system at multiple spatial and temporal scales; (2) develop tools that can assist traffic engineers in monitoring, assessing, and responding to transportation conditions in both real time and extended time periods; and (3) demonstrate the advantages at integrating analysis and visualization at different scales.

We present analysis and visualization tools to quickly understand current traffic conditions while also characterizing broader objectives for energy/fuel use, emissions, traffic congestion, service consistency, and other metrics extracted from the available data. It is expected that the tool can also be used to conduct analyses that will inform planning decisions for infrastructure and technology deployment. We describe a number of visualizations that have been developed and indicate the direction of future plans within ORNL's Digital Twin tool.

Study Area

The study area for this work is a shopping district in Chattanooga, Tennessee. It is located east of I-75, approximately 2-3 miles north of the I-24/I-75 interchange. The area stretches from Igou Gap Road in the South to Shallowford Road in the North, along both sides of Gunbarrel Road and Shallowford Road. West of Gunbarrel Road, there is a large shopping mall, as well as many restaurants and other businesses. East of Gunbarrel Road, there is a strip mall, two large grocery stores, various other large stores, and a movie theater. Along Shallowford Road, there are hotels, restaurants, and gas stations.

The shopping district is accessible via two highway exits: Hamilton Place Boulevard (exit 4A) and Shallowford Road (exit 5). Lee Highway, another major arterial in the area, is about 1/2 mile west of and approximately parallel to I-75 in this region. Shallowford Road intersects both Lee Highway and I-75 and carries a significant volume of traffic between these highways and the shopping district.

Figure 1. Overview of the Chattanooga Metropolitan Area with a close-up on the study area for this paper: a shopping district in the Shallowford Road area. The map includes sensor locations for two of the data sources for this paper: radar sensors (blue) along the highways and camera-based sensors (orange) on some of the city's intersections.

Data Sources

Multiple data sources are combined in the Digital Twin tool to integrate transportation data from disparate systems and make them available in one place. This enables data analytics capabilities that can yield improved ease of use, as well as providing new insights into the transportation system to traffic engineers and transportation planners and managers. The following describes several of the data sources currently integrated in the tool.

Intersection Cameras The City of Chattanooga has a growing number of traffic signal camera-based sensors (71 at the time of writing) at many of the city's intersections. Each sensor uses a fish-eye camera lens that is mounted 9-12 meters (30-40 feet) above the intersection (ideally close to its center) to observe traffic approaching from all directions and passing through the intersection. With optimal configuration, the camera can track vehicles within a radius of 60 meters (200 feet) or more. The RGB images are captured at a rate of 10 frames per second with a resolution of 1280×960 pixels, and the camera software offers projection between a circular representation of the fisheye view (moderately distorted) and a much less distorted view that is closer to cross-shaped for most intersections (both versions fill any empty space with black). During nighttime, detection is based on headlights, and the camera software offers a low visibility warning if detection is not possible with sufficient confidence due to poor visibility (e.g. fog, heavy rain, dirty camera lens). The camera-based system provides extracts of a vast array of traffic data in real time. Data processing of the video images is used to compute vehicle-level information such as length, speed, current traffic light state (red/yellow/green), wait time on red, approach direction, and turn direction at sub-second resolution. The camera-based sensing system is also directly connected to the traffic signal controller at the intersection and provides signals to the controller for actuation of traffic signal phase and timing (SPaT). The camera sensing system also receives data back from the controller, so a common interface can be used to obtain vehicle/traffic data derived from the sensors in addition to tracking SPaT data.

Radar Sensors The Tennessee Department of Transportation (TDOT) manages and maintains 214 Radar Sensors in the Chattanooga area. The sensors are placed about half a mile apart along the highways through urban areas, and they report aggregate vehicle counts and average speeds for each lane at 30-second intervals. Typically, the sensors are placed on each side of a highway, such that each delivers data for one direction of traffic. However, this is not always the case, particularly at highway junctions, where traffic splits off into different directions. At the time of writing this paper, radar sensor data is provided as daily updates, such that real-time display is not yet possible, but a real-time API is under development by TDOT.

Web Framework

The visualizations in this work were developed to be part of *CTwin*, a situational awareness web platform for the digital twin of Chattanooga, Tennessee. CTwin integrates data from a variety of sources, such as the intersection cameras and radar sensors used in this paper, as well as several sources for traffic incidents, traffic jams and alerts from Waze, weather, and many static sources such as map layers for road networks and points of interest (e.g. hospitals, schools, etc.). Different components of the platform, such as frontend, backend, and microservices run in separate docker containers. The backend is written in Java. On the front end, we adopt Angular, a web framework implemented with the Model-View-Viewmodel (MVVM) design pattern, to structurally organize multiple user workflows and user interfaces in a component-based fashion. This approach aims to ensure the platform's maintainability. The web map is created using the OpenLayers JavaScript mapping library, and the charts in the live version of the tool are developed using Highcharts and D3.js. These libraries provide many nice interactive qualities, including detailed information on hover-overs and the coordination between multiple charts, meanwhile offers the flexibility for creating novel data visualizations (e.g., linked chars and innovative visual representations). Some figures in this paper show visualizations from python prototypes, and very similar Javascript-based versions were integrated in CTwin after the submission of the paper.

Visualizations CTwin is organized in tabs that are grouped by topic. Each tab contains a dashboard that provides insights about a specific aspect of traffic. The landing page provides a high-level overview, such as regional volumes and speeds, current traffic incidents, a weather forecast for the next 48 hours, and basic information about the tool. A map presents all geospatial visualizations, including map layers for sensor locations that display each sensor's data as a hover-over and (when clicked) multiple visualizations for this sensor's data in a side bar. The corridor tab shows corridor-level visualizations as well as visualizations for individual sensors that are part of the corridor. These visualizations include the chord diagrams presented in this paper, as well as simple line charts such as volume by approach direction. This is achieved by defining a bounding polygon around the corridor, and applying a geospatial filter to include only the relevant sensors for each corridor. An incidents tab provides in-depth visualizations of traffic incidents. Finally, the metrics tab provides different metrics, including the fuel use and energy cost visualizations presented in this paper.

Data Management All sensor data is processed and stored in a PostgreSQL database. Data ingestion is possible in real-time, as well as for historic data, and processing includes aggregations to different time-intervals (daily, hourly, etc), and by different parameters (approach direction, turn movements) to save processing time and provide a responsive system. These aggregations are necessary to keep the system responsive: a single day of raw radar sensor data is 2 GB in size, and a single day of vehicle-level data from the camera-based sensors is about 1 GB in size (varies between 500 MB and 1.5 GB depending on traffic volumes). To provide additional aggregations, we have to create a new table and populate it. This aggregation step is carried out every time new data is added to the system. This additional effort is well worth the result – by pre-aggregating the data, we have achieved rendering times of well under a second for most charts, and about one second for the most compute-intensive chart (see Figure 4).

On top of the database layer, microservices provide functions to access the data in a visualization-ready format. These microservices serve data for a specified timeframe and temporal resolution specified in a query. By default, it returns hourly data for a full day (for historic data) or up to the current time (for real-time data). The user interface currently only provides a choice of day; however, we are planning an extension to support more user choices, such as the time interval or temporal resolution, which will be available in a later version of CTwin.

Data Quality Data quality is a common issue in any type of measured data. Some sensors malfunction and record implausible measurements (e.g. speeds over 200 mph). For this type of data quality issues, we rely on our expert users to recognize suspicious data. Missing data is another common problem. We address this problem by adapting charts to ensure that the x-axis always includes the entire time range (24 hours) and that the data is timestamped appropriately. Gaps in data availability will show up as gaps in any line charts. Other chart types, such as the chord diagram, are shown side-by-side with line charts, so gaps in the data are clear from context, even if the chart itself does not visualize them. If there is no data for an entire day, the chart is replaced with a text indicating the lack of data.

Microscale Analysis and Visualization

For the purpose of this paper, we define *microscale* analysis as one corresponding to a very small area of the transportation system, such as at a single intersection, or a single sensor. There are two sensor types in our study area for which we can conduct microscale analysis: intersection cameras and radar sensors.

Visualizing Turn Movements for Individual Intersections

Our main data source for intersection-level visualization is provided by the traffic signal camera-based sensors. For each intersection, we have information for each vehicle that traverses the intersection. For the purpose of this paper, we focus primarily on the vehicles' approaching directions and turn movements. The directions associated with all traffic signal camera-based sensors in Chattanooga are always defined using the cardinal directions: North, South, East, and West.

Traditionally, traffic flow through an intersection is provided as turn diagrams, as seen in the Signal Timing Manual Urbanik et al. (2015). This method of visualization has the advantage of giving a detailed diagram of the intersection's lanes; however, the volumes per turn movement are represented by just numbers and, in some cases, color. Another way to visualize flow is using line charts to visualize volume by approach direction or destination, but this would make it difficult to correlate the two. Heatmaps are useful to see correlations, but they cannot provide the spatial relationship between the different directions.

Other approaches Guo et al. (2011) include the visualization of individual turn movement trajectories combined with modified histograms in a ring around the intersection view. While this gives users a sense of specific trajectories, this type of visualization does not provide an intuitive representation of turn movements as the individual trajectories overlay.

We propose an interactive combined view that provides spatial relations, connection of origins and destinations, and relative volumes, with optional numeric values as pop-up. This combined view serves to provide a deeper analysis of turn movements and relative traffic volumes for a selected time frame, e.g. a day, or the morning/evening peak hours. This view can also be used to compare traffic movements during different light phases, or even to compare different traffic light control strategies if the corresponding days or time frames are known to the user.

Designing Chord Diagrams for Turn Movement Visualization The chosen representation is a *chord diagram* Bostock (2018). Chord diagrams are powerful tools to display relations, as well as movement between different regions Zeng et al. (2013). The top section of Figure 2 displays different views of traffic at the intersection of Gunbarrel Road & Hamilton Place Boulevard under different user interactions/mouse-overs. This intersection connects Gunbarrel Road to a large indoor mall on the West side of the road, and a large strip mall on the East side of the road. In the leftmost chart, several *arcs* and *bands* are labeled to clarify terminology.

Each *arc* on the circle represents a cardinal direction, and the size of the arc represents the proportion of traffic originated from that direction. For instance, one can see that the majority of traffic is on the main road (Gunbarrel), from the North (blue) and the South (purple), whose arcs each cover about a third of the circle. The mall to the West of the intersection has more originating traffic than the one to the East, as seen from the larger brown arc and the smaller orange arc.

Each *band* between arcs represents traffic that has its origin on one arc and its destination on the other. The width of the band is determined by the volume originating from the corresponding direction. The more asymmetrical the traffic flow is, the more the band will taper towards the direction of the origin with fewer vehicles. The band color is determined by the more dominant originating direction. For example, the North and South arcs are connected by a wide purple band, which is by far the thickest band in the chart. This means that the main traffic flow is between North and South. The band is purple because there is more traffic from South to North than from North to South.

The width of the bands on each end is determined by the relative amount of traffic between the different pairs of directions. The fact that approximately half of the traffic from the brown arc is connected to the purple arc indicates that about half of the traffic from the West turned South at this intersection. The remaining half from the West splits approximately equally between North and East. It is interesting to note that all bands originated from the West are brown, indicating that there is more traffic originating from the West than to it. This can be explained by different factors:

- There are multiple roads to access the West mall, including a highway exit providing direct access from I-75 to this mall.
- Gunbarrel Road provides access to many other businesses, including a variety of restaurants and multiple major grocery stores, which may be a desirable stop on the way home from a shopping trip.

On mouse-over, the diagram provides additional information about the band or arc in a pop-up. It also hides all bands that are not relevant to the most recently selected arc. The main interaction methods for this chart type are the following:

- Select data based on date range, time range, and other variables such as traffic light phase, speed, or vehicle length.
- Mouse-over on an arc reveals the number of vehicles originating from this direction.
- Mouse-over on a band reveals the number of vehicles flowing between two arcs, split by direction of traffic flow.

One major consideration for the intersection-level visualizations was the choice of colors used to represent the different directions. Not only do red, yellow, and green already have pre-established meaning, but they are also difficult to distinguish for individuals with Protanopia or Deuteranopia, two common types of colorblindness. To avoid misunderstandings and provide a clearer visualization, we chose to avoid these colors. We chose cool colors (blue and purple) for North and South, and warm colors (brown and orange) for West and East. Using colors in the same color family highlights the geographic similarity between each pair of cardinal directions, while having different color families for cross traffic highlights the differences in traffic flow. Furthermore, we chose colors that can be distinguished by colorblind individuals. This was tested using Coblis, a color blindness simulator Daniel "Colblindor" Flück (2019) and adjusted based on feedback from a colorblind user.

Figure 2. Chord charts for intersection-level visualization for a single day (Tuesday, April 2, 2019). The *interactions* section demonstrates the chart's interactive options for mouse-over on the arcs and bands. In the middle section, the horizontally placed charts represent the intersections on Shallowford Road, and the vertically placed charts represent the intersections on Gunbarrel Road. The bottom sections provide examples for different *traffic light colors* and *times of day* for two key intersections.

Overall, chord diagrams are more challenging to read than a line chart. However, their main strength lies in conveying an intersection's traffic flow characteristics at a glance while also representing the spatial connection between the different origin directions.

Analyzing a District's Turn Movements The middle section of Figure 2 shows a hybrid microscale/mesoscale visualization of all intersection sensors on the Shallowford Road and Gunbarrel Road corridors arranged according to their spatial relation to each other. There are six intersections on Shallowford Road, which runs approximately from West to East (displayed horizontally), and three intersections on Gunbarrel Road, which runs approximately North to South (displayed vertically), with one shared intersection.

The chord charts demonstrate significant differences in traffic flow in this area. As one would expect, orange and brown dominate charts on Shallowford Road and purple and blue dominate charts on Gunbarrel Road. The shared intersection is one of the most well-balanced intersections in this area. The intersections can be classified into the following groups:

- *Two major roads or points of interest on different sides of a major road*: there is a significant amount of traffic originating from all four directions, so all four colors appear prominently in the chart. Intersections in this category are Shallowford Rd & Gunbarrel Rd and Gunbarrel Rd & Hamilton Place Blvd.
- *Highway ramps or one-way major roads*: these intersections have a large amount of traffic originating from the off-ramp of I-75 and both directions on Shallowford Road, but none from the on-ramp. Three colors appear prominently, and one color is only visible as a single short line that receives a lot of traffic from other directions.
- *Minor side streets*: these intersections are strongly dominated by the primary traffic direction (Shallowford Road or Gunbarrel Road), and traffic to and from these minor side streets only contributes a minimal amount to the overall traffic volume. Amin Drive, Napier Rd, Lifestyle Way, and McCutcheon Road

intersections fall in this category. All of these intersections are dominated by a single color: the three intersections on Shallowford Road are mostly orange and McCutcheon is mostly blue.

Analyzing Driving Behavior During Different Traffic Light Colors The *Traffic Light Colors* section in the bottom section of Figure 2 visualizes turn movements for two key intersections during different traffic light colors at the time each vehicle entered the intersection. These two intersections both fall into the first group of intersections: Shallowford Road & Gunbarrel Road is an intersection of two major roads, and Gunbarrel Road & Hamilton Place Boulevard connects points of interest (i.e., shopping malls) on different sides of a major road.

During a *green* traffic light, the diagram looks very similar to the diagram for all traffic at the intersection. This is expected as the majority of traffic should flow through the intersection while the light is green.

During a *yellow* traffic light, the diagrams look moderately similar, but there are some noticeable differences. For the Shallowford & Gunbarrel intersection, the biggest difference lies in its left-turning traffic. Although the band from West to North was very slim during the green light, it grew substantially wider during the yellow light. A similar effect can be observed in the left turn band from East to South. This could be an indicator that the protected left turn phase is not long enough to keep up with traffic volumes, and many left turn vehicles were only able to make the turn during the yellow light. For the Gunbarrel & Hamilton intersection, this effect is most obvious for left turns from North to East. Notably, right-turns from West to South at the Gunbarrel & Hamilton intersection also represent an increased portion of the traffic. At a larger scale, while there is more Northbound than Southbound traffic on Gunbarrel Road, Southbound traffic proceeds through yellow lights proportionally more frequently.

During a *red* traffic light, one can see significant differences in the diagram. Unsurprisingly, the largest proportion of turn movements during a red light is right turn movements, which are permitted on red for these two intersections. For the remaining traffic, the majority of vehicles running red lights are headed straight. This is much more frequent for Eastbound traffic than Westbound traffic (measured by the width of the band on each end), but relatively similar for Northbound and Southbound traffic.

Comparing Turn Movement Changes Between Different Times of Day The *Time of Day* section in the bottom section of Figure 2 provides a comparison of turn movements for different times of day for the same two key intersections. Table 1 lists the hours assigned to each time of day.

Table 1. Timespan for each defined time of day.

Time of Day	Hours
Early Morning	Midnight – 6 a.m.
Morning	6 a.m. – 10 a.m.
Mid-Day	10 a.m. – 3 p.m.
Evening	3 p.m. – 7 p.m.
Night	7 p.m. – Midnight

During typical shopping hours (mid-day and evening), the turn movements look almost identical to the full-day version of the chart. However, for traffic during other times of day, the turn movement patterns look different.

For Shallowford Road & Gunbarrel Road, morning traffic is dominated by traffic flow from residential neighborhoods in the East towards I-75 and Lee Highway in the West. Between West and South, there is more traffic originating West in the early morning and morning hours, but more traffic from the South from mid-day to the end of the day.

For Gunbarrel Road & Hamilton Place Boulevard, there is much more traffic from the South during main shopping hours and much more from the North outside of these hours. During early morning hours, the largest number of turn movements is from East (which has a 24-hour grocery store) to South, whereas at night, the largest number is from West (which has several restaurants in addition to the mall) to South.

Visualization and Analysis of Highway Traffic Flow

Up to a "handful" of sensors, one can combine multiple individual microscale visualizations into a hybrid microscale/mesoscale visualization. For a small number of sensors, one can compare individual values and see patterns between different sensors; however, with increasing numbers of sensors, this type of visualization becomes overwhelming. In this section, we classify these hybrid visualizations as microscale since the focus of the visualizations is to study each individual sensor rather than the system as a whole or the interplay between them.

The following is an example of a hybrid microscale/mesoscale visualization for a group of Radar sensors along I-75. As seen in Figure 1, there are four Radar Sensors on each side of the segment of I-75 that passes adjacent to the study shopping district. Each sensor provides lane-level data for average speeds, volumes, and occupancy, aggregated over 30-second intervals.

Figure 3 shows a visualization of data from November 2018 to March 2019 for these sensors, split by travel direction that is indicated by the arrows. The sensors are organized in rows by direction of flow, with one type of data per column: speed (left), volume (middle) and occupancy (right). Each chart displays the mean value across all lanes as a red line and the inner 90^{th} percentile as a gray band. To provide additional context, the position of Shallowford Road and the on-ramp from the shopping mall onto I-75 South are plotted between the columns. There is no northbound on-ramp from the shopping mall.

Figure 3. Visualization of raw sensor data from Radar Sensors for the I-75 segment that runs through the shopping district. The arrows indicate traffic flow direction between sensors (Southbound on the left, Northbound on the right). There are three charts per sensor: speed (left), volume (middle), and occupancy (right), each with a dark red line representing average values, and a gray band representing the inner 90th percentile. For additional context, ramps are added for Shallowford Road (both directions) and Hamilton Place Boulevard (I-75S only).

From these charts, one can see a clear diurnal distribution of volume and occupancy over the course of 24 hours. The most interesting time period is the evening peak: minimum speeds drop for almost all sensor locations. The sensor at 4.8 miles South (bottom row of the Southbound sensors) demonstrates the most significant impact: minimum speeds drop to 30 miles per hour within the inner 90th percentile band, while occupancy simultaneously peaks. This indicates that slower vehicles merging onto the highway from the on-ramp near the shopping mall may lead to increased congestion. The trough observed in mean speeds at the southbound sensor at mile 6.0 is likely due to congestion of traffic exiting the highway onto Shallowford Road, where vehicles must often stop at a traffic signal. The same slowdown is not observed for the on-ramp to the highway south of Shallowford Road, as traffic here is likely able to freely accelerate downhill before entering the highway.

Figure 3 also shows directionality of traffic flow, where the morning peak is more prominent in southbound (towards downtown) volume counts and the evening peak is more prominent in northbound (from downtown) volume counts.

Mesoscale Analysis and Visualization

For *mesoscale analysis*, we consider individual corridors, or contiguous areas which have a shared meaning or purpose, such as a shopping district. The intent behind this definition is to bridge the gap between *microscale*, which only considers individual sensors or data points, and *macroscale*, which is so large that many interesting aspects of an area may be masked as a result of combining large volumes of data. For instance, there could be an incident on one of the highways, but, unless this incident was very extreme, the reduction in average speeds would barely register when aggregated to an entire metropolitan region. On the other hand, monitoring one individual sensor is also insufficient at assessing the scale of the traffic jam. Mesoscale analysis enables evaluation at a level that can provide insight into the behavior/performance of the transportation system over a specific region of interest to the user.

Corridor-Level Traffic Flow

As an example of a corridor-level visualization, we present the traffic flow from multiple sensors located along a corridor in one single chart. To achieve this, we placed sensors from one end of the corridor to the other along the x-axis. We further enhanced the representation of physical distance by spacing the ticks for the sensors according to the relative distance among them. For each intersection, we determine the total flow departing the intersection in each direction. We plot the mean volume per time interval (e.g. an hour) as a line and shade the inner 80th percentile with a semitransparent version of the line color. For each cardinal direction, we use the same colors previously introduced for the chord diagrams for consistency.

Figure 3 presents a visualization of traffic flow along the Shallowford Road corridor. Each line represents the average hourly flow going in the corresponding direction, and the bands represent the 80th percentile within the selected time frame (full day or time of day). Comparing the different time frames provided in Figure 4, one can see clear differences in traffic flow patterns.

Figure 4. Different views of the Shallowford Road Corridor on Tuesday, April 2 with a confidence interval of 80%. We showcase the entire day (top left), as well as variation in traffic flow patterns throughout different times of day: early morning (top right), morning (middle left), mid-day (middle right), evening (bottom left), and night (bottom right). Definitions for different times of day can be found in Table 1.

From the high volumes in the orange and brown bands and the low volumes in the blue and purple bands, one can tell at a glance that this corridor is a major roadway along East and West directions, intersecting with a variety of minor roads in between.

Major Crossroads Gunbarrel Road can be identified clearly as a major crossroad as the traffic is nearly balanced in all four cardinal directions. Southbound has a particularly large volume of traffic from mid-day to evening (typical shopping hours) due to the shopping malls that can be accessed. Northbound traffic only surpasses Southbound traffic at night and in the early morning, which is likely because the road leads to a residential area. During the day, the road also serves as an access to an alternate route to avoid congestion on Shallowford Road. During typical work hours, there is much more Westbound traffic than Eastbound traffic, as this direction provides access to I-75, many businesses, and Lee Highway. In the evening and early morning, the flow is approximately the same. This, too, can be explained by the large residential neighborhood North and East of the intersection.

Shopping Mall Traffic Flow at Napier Road The intersection at Napier Road has some noticeable traffic fluctuations. Westbound traffic peaks at Napier Road throughout most of the day, with the exception of morning traffic which is consistently high across all intersections but has a slight dip at Napier Road. Much of the additional traffic is left-turn traffic from the south end of the intersection. Similarly, Eastbound traffic drops at Napier Road, most noticeably in the early morning and morning hours. Much of this traffic likely comes directly from the I-75N off-ramp, as there are two dedicated off-ramp lanes that lead directly to right-turn-only lanes onto Napier Road.

There are three things to note about this intersection: first of all, a lot of morning traffic could be explained by a drive-through coffee shop that opens early in the morning and closes late at night. Second, it is an access point to a lot of the local businesses. Finally, it also serves as access to alternate routes to Gunbarrel Road and to I-75S when traffic on Shallowford Road is congested.

Highway Access The I-75S and I-75N on-ramps can be identified easily because they have no traffic in the opposite direction, as expected for a highway ramp or a one-way street. Overall, there is more traffic flowing onto I-75S than onto I-75N, which makes sense given that the shopping district is located close to the edge of the metropolitan area, and I-75S leads towards downtown Chattanooga.

This corridor visualization could be adapted in two different ways:

- Modify to accommodate data from radar sensors: each sensor only provides data for one direction but multiple lanes. Any reduction in vehicle counts between sensors could be correlated or fused with highway exits on the way.
- Create the inverse chart: instead of focusing on the direction to flow is headed, one could instead focus on the flow's origin direction.

Macroscale Analysis and Visualization

At macroscale, we provide an overview of highway speeds and volumes as colored lines on the map and as interactive charts. In addition, we present metrics for fuel use and energy cost.

Highway Traffic Flow

We visualize highway traffic flow by coloring road segments based on traffic information, similar to what one would see in a navigation tool. However, rather than using probe data from vehicles in motion, we use volume and speed information from stationary radar sensors along the highways.

To achieve this, we mapped each radar sensor to the appropriate nearby road segments, i.e., road segments for the highways that are heading in the correct direction and are closer to this radar sensor than any other one. Since the road network provided by the Chattanooga Department of Transportation comes segmented into multiple pieces of various lengths (ranging from 13 m to 1,068 m), a spatial join was performed to assign the nearest radar sensor ID to each road network segment. The roads with radar sensors (US-27, I-24, I-75, and TN-153) were extracted from the full network and spatially joined to the appropriate radar sensors.

We then aggregate the speeds and volumes for each radar sensor to the desired time frame (e.g., specific day, hour, etc.) and color the road segment accordingly. Figure 5 demonstrates visualizations for minimum speeds and total volumes for the entire day of February 8, 2020.

Figure 5. Highway speeds (top) and volumes (bottom) in the Chattanooga Metropolitan Area, visualized as colorful lines based on radar sensor data.

Aggregated Regional Speed and Volumes

At region-level, we provide a combined visualization of speeds and volumes from radar data for the region's highways. We determine average speeds and volumes in the entire region at 5-minute intervals. We plot the aggregated traffic volume as a line with filled in integral to represent the volume. The mean speed is provided as a red line, and the inner 90^{th} percentile is shaded in as a gray band. The same type of visualization can be applied for a single sensor, a corridor, or a district to provide comparison of traffic speeds and volumes in different locations.

Speeds and volumes can also be merged with the road network to create visualizations of traffic conditions using colored road segments on a map, as often seen in routing and navigation systems.

The top row in Figure 6 shows the regional speed and volume for the Chattanooga Metropolitan Area on a Tuesday (November 5, 2019) at 5-minute intervals. Upon mouse-over, a pop-up appears with detailed numeric information about the selected time.

Figure 6. Radar sensor-based data aggregated to 5-minute intervals for the Chattanooga Metropolitan Area. Top row: Speeds and volumes with mouse-over information. Bottom row: fuel use per vehicle mile traveled (left) and cost per vehicle mile traveled (right).

Fuel Economy Visualization

We compute fuel economy and cost metrics based on the observed speed recorded from the Radar Sensors. The fuel usage metric is derived based on the non-linear relationship between vehicle speed and fuel usage as documented by the Transportation Energy Data Book Davis et al. (2002). It is further converted into fuel cost based on the assumption that fuel costs $3 per gallon. Based on these assumptions, the plots below demonstrate the daily temporal heterogeneity in both fuel usage and costs in the City of Chattanooga.

The left chart in Figure 7 provides fuel use for the region. One can see that the 5^{th} percentile fuel use drops to near-zero during peak travel hours while the 95^{th} percentile is very stable throughout the day with only a slight dip in the early morning hours.

The right chart in Figure 7 offers energy cost for the same time frame. The 5^{th} percentile energy cost per VMT is very stable, but the 95^{th} percentile peaks around twice the usual energy cost.

Both of these visualizations could be adapted to a smaller scale by only including data from a subset of sensors.

Figure 7. Fuel economy visualization based on radar sensor data which was aggregated to 5 minute intervals for Chattanooga Metropolitan Area: Fuel use per vehicle mile traveled (left), and cost per vehicle mile traveled (right).

Conclusion

We have demonstrated a wide range of techniques for transportation visualization at different scales with the example of a shopping district in Chattanooga, Tennessee.

At microscale, we have presented a turn-movement visualization that uses a chord diagram. While this visualization requires some training, it is a powerful tool to analyze and compare turn movements for an intersection. We have further included a more traditional visualization of data from individual radar sensors in a hybrid micro/mesoscale visualization. Additional context was provided in the form of arrows to indicate the direction of traffic flow and roads to indicate the location of off-ramps and on-ramps. At mesoscale, we have introduced a corridor visualization for traffic flow among intersections, which represents all directions of traffic flow in one diagram. Finally, we presented a variety of visualizations at macroscale: a full map view can display highway speeds and volumes at regional scale for a given time slice, regional volumes and speeds aggregated to 5-minute intervals, and fuel use and energy cost per vehicle mile traveled.

In the future, we are planning to add more data sources to the tool, including freight data, traffic controller data, and emulated and simulated traffic flow. Moreover, we will provide more analytics, such as Moving Ahead for Progress in the 21st century (MAP-21) performance metrics Federal Highway Association (2019b), and Automated Traffic Signal Performance Measures (ATSPMs) Federal Highway Association (2019a) along with more visualizations. For many metrics, it is beneficial to examine data at different scales, such as presented in this paper. This increases the understanding of traffic flow and bottlenecks in the area. A better understanding of traffic flow and freight movements can also be very beneficial to reduce congestion, increase safety, and reduce energy consumption through adapting control strategies, such as signal timing or dynamic traffic routing. Finally, an understanding of traffic flow can improve the operation of connected automated vehicles through infrastructure-to-vehicle and vehicle-to-vehicle communications.

Acknowledgements

This work was supported by the U.S. Department of Energy (U.S DOE), Office of Energy Efficiency and Renewable Energy, Vehicle Technologies Office We thank the Chattanooga Department of Transportation for their guidance on choosing an arterial, and providing intersection sensor data, and the Tennessee Department of Transportation for providing radar data. Finally, we would like to thank the Department of Energy Vehicle Technologies office and Oak Ridge National Laboratory for funding this work.

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