

Telematics: Review and Applications in Freight Transportation

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Yunfei Ma

First-year master's/incoming PhD Student at CSE, McMaster University

Supervisor: Elkafi Hassini, Saiedeh Razavi

Transportation Data Visualization with a Focus on Freight: A Literature Review --Manuscript Draft--

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Corresponding Author:	Yunfei Ma, M.Sc. McMaster University Hamilton, ON CANADA
First Author:	Yunfei Ma, M.S.c
Order of Authors:	Yunfei Ma, M.S.c Amir M Amiri, Postdoc Elkafi Hassini, Professor Saiedeh Razavi, Associate Professor
Abstract:	<p>Road-based freight movements are a critical component of the supply chain and transportation networks, especially for the middle and last-mile distribution stages. With the drive to invest in big data collection capabilities, most of the collected freight movement data remains underutilized. To improve the efficiency and resiliency of the supply chain, it is essential to enhance the visibility of goods movements on road networks. This can be done by visualizing the different aspects of goods movement patterns using the data collected from telematics devices installed in commercial vehicles. Given the recent development in data visualization and collection technologies, there is a need to conduct a critical literature review in this nascent and increasingly important field of study to identify gaps in the literature and propose future research and policy directions. To this end, we provide in this paper a comprehensive literature review on this topic and analyze the previous research from different perspectives, such as data levels of abstraction and existing visualization techniques. In addition, we provide a taxonomy of freight transportation visualization according to the underlying analytic objective. Furthermore, we propose a decision support tool to aid freight data analysts in selecting the right visualization tools. Finally, we identify research gaps in the field of freight transportation visualization.</p>

Telematics data visualization taxonomy

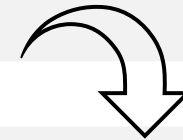


Introduction - telematics data



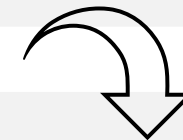
Level of abstraction

Data aggregation
Objectives



Visualization
techniques

Space
Time
Event



Conclusion - decision-maker analysis

Developments in telematics



Advanced telematics devices



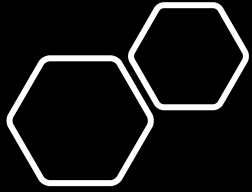
Telematics data precision



Real time exchange of data through internet



Cloud-based storage



Significance of Data Visualization



Human intelligence

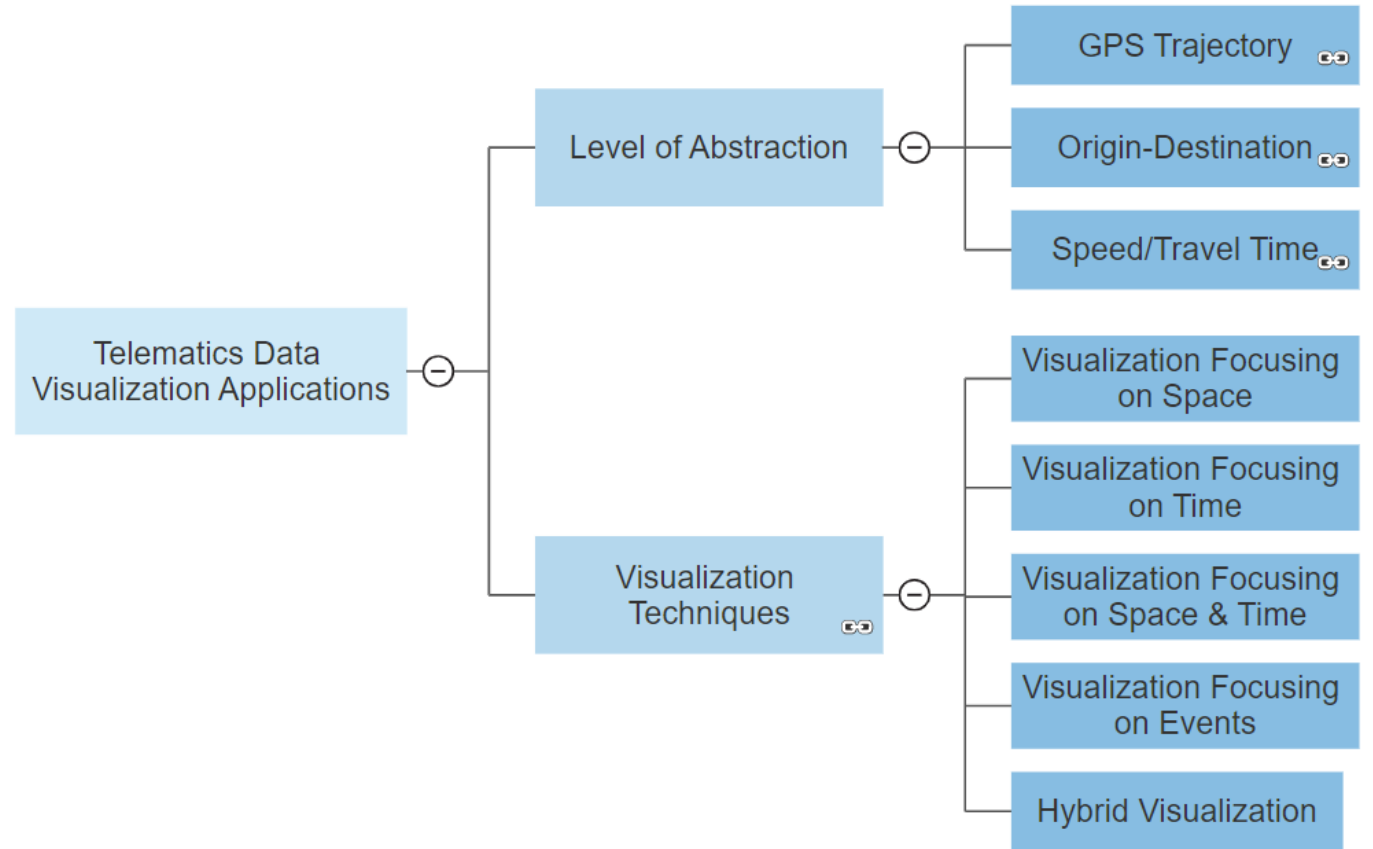


Computation & Analytics

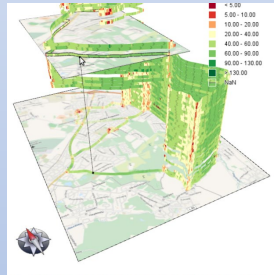


Source: [Tesla AI Day](#)

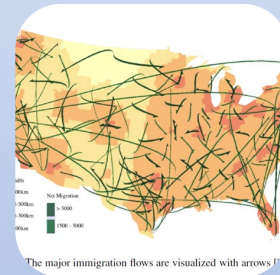
Taxonomy For Telematics Data Visualization



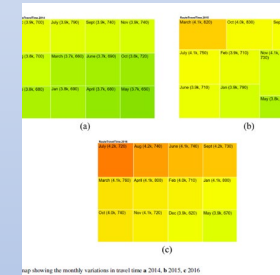
Level of Abstraction



GPS Trajectory



Origin-Destination
(OD)



Speed/Travel Time

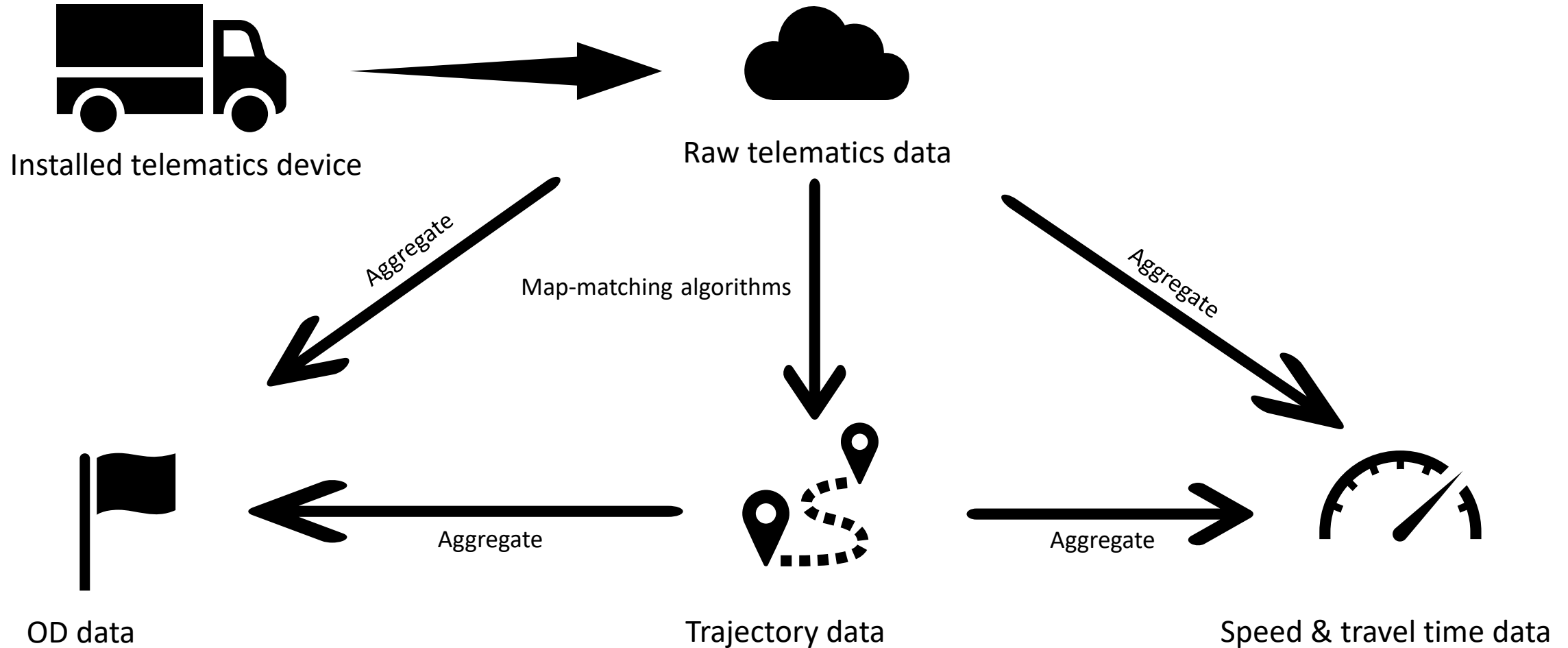
Raw Telematic Data

Table 1 Sample of reduced raw data obtained from the GPS devices

Device ID	Latitude	Longitude	Reporting time
45214[REDACTED]	13.08826	80.28201	07:29:35
45214[REDACTED]	13.0882	80.28197	07:29:40
45214[REDACTED]	13.08809	80.28165	07:29:45
452149[REDACTED]	13.08787	80.28145	07:29:50
452149[REDACTED]	13.08751	80.28136	07:29:55
452149[REDACTED]	13.08711	80.28126	07:30:00
452149[REDACTED]	13.08674	80.28117	07:30:05
452149[REDACTED]	13.08645	80.28108	07:30:10

Source: Gracious, R., Kumar, B. A., & Vanajakshi, L. (2020). Characterizing bus travel time using advanced data visualization techniques

Data Aggregation



Objectives – Trajectory

Traffic Jam

Trajectory
Clustering

Monitor Large-
scale
Trajectory Data

Visualization of
transportation
patterns

Multiple Route
Choices

Objectives – Origin and destination

Mass Rapid Transit
Monitoring

Travel-to-work Flow

Immigration/Goods
Flow

Exploration of
Urban Function

Traffic Dynamic
Exploration

Objectives – Speed & Travel Time



Characterizing
Movers' Travel Time



Co-Occurrence
Pattern



Bottleneck Analysis

Visualization Techniques



SPACE



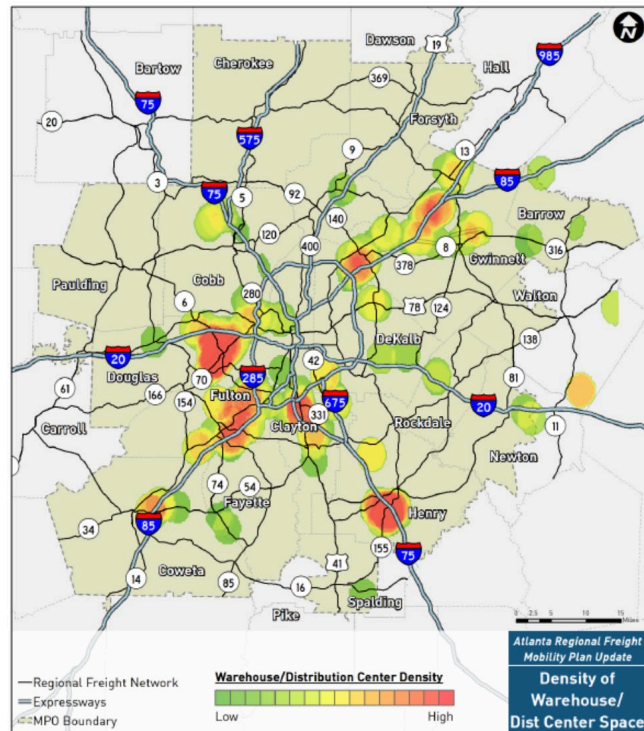
TIME



EVENTS



Visualization focusing on space



Source: Georgia Power Company. Consultant analysis



Fig. 6. Visualization of hot spots in a city through the heatmap technique [75]. The red regions represent high volume of traffic, whereas the blue regions indicate low volume of traffic.

Source: Chen, W., Guo, F., & Wang, F.-Y. (2015). A survey of Traffic Data Visualization.

Visualization focusing on space – OD

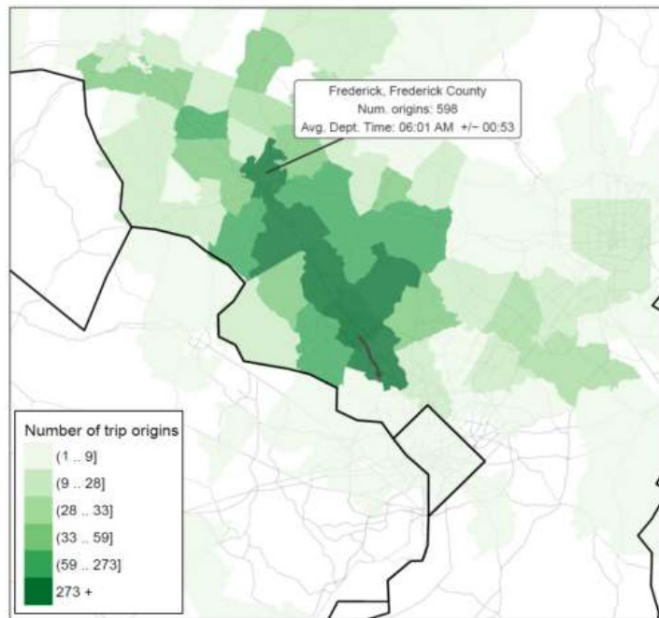


Figure 5. Sub-County Level Origins

Source: Petrone, A., & Franz, M. L. (2018). Probe vehicle based trajectory data visualization and applications.

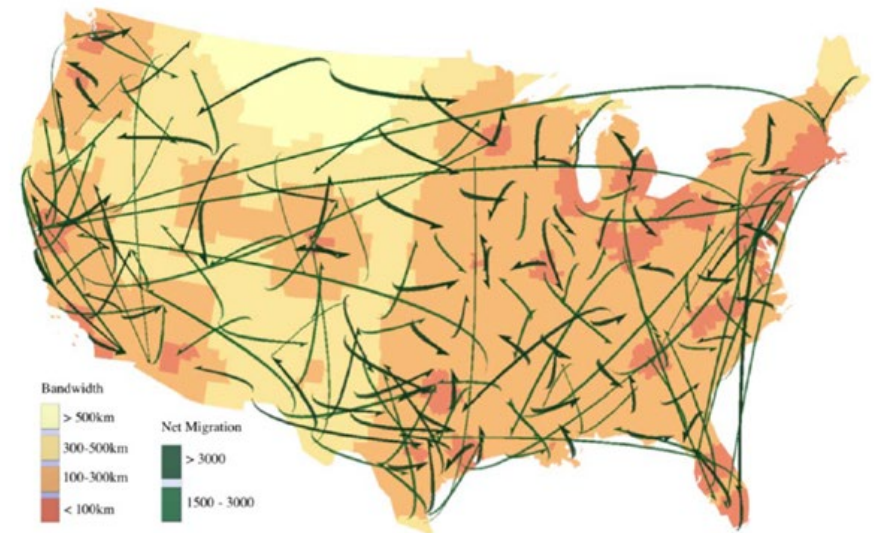


Fig. 9. The major immigration flows are visualized with arrows [82].

Source: Chen, W., Guo, F., & Wang, F.-Y. (2015). A survey of Traffic Data Visualization.

Visualization focusing on time

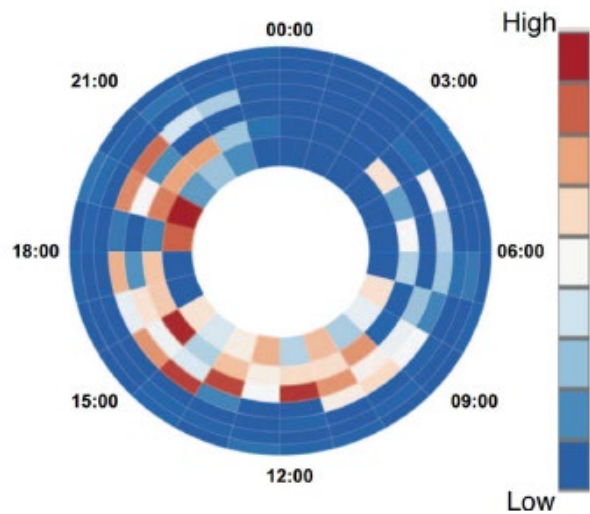


Fig. 3. Visualizing periodic time in radial layout [11]. Time in a day is shown on the circular axis and each ring represents a day. The sector color represents a selected traffic quantity with the color map shown on the right.

Source: Chen, W., Guo, F., & Wang, F.-Y. (2015). A survey of Traffic Data Visualization.

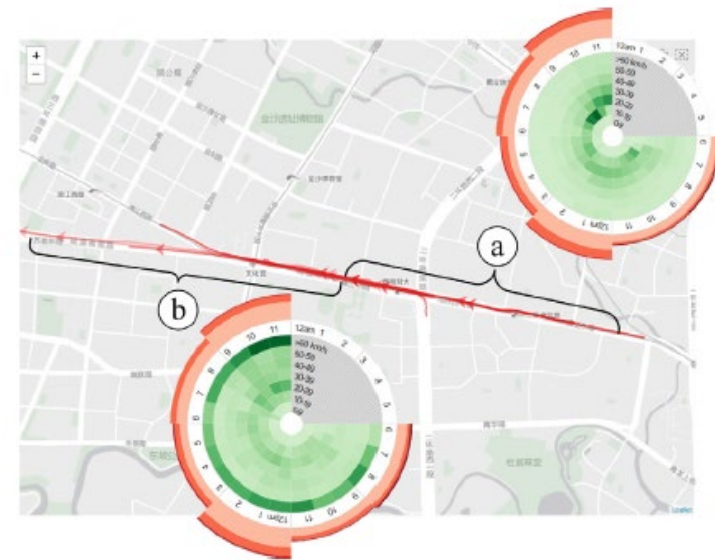


Fig. 7. Traffic congestion analysis. The average speed is within 20 km/h from Qingjiang East Road to Chengwen Elevated Road (a) while more than 60 km/h after Chengwen Elevated Road (b).

Source: Jin, S., Tao, Y., Yan, Y., Xu, J., & Lin, H. (2019). Visual analytics of taxi trajectory data via topical sub-trajectories.

Visualization focusing on events

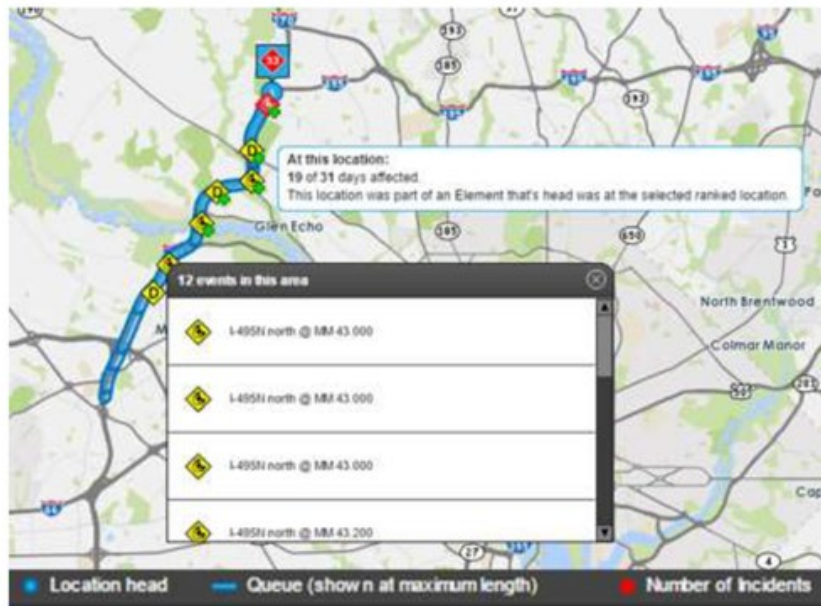


Figure 6. Bottleneck Map

Source: Franz, M. L., Pack, M. L., Lund, D., & Plaisant, C. (2017). Visualization tools for traffic bottleneck analysis.

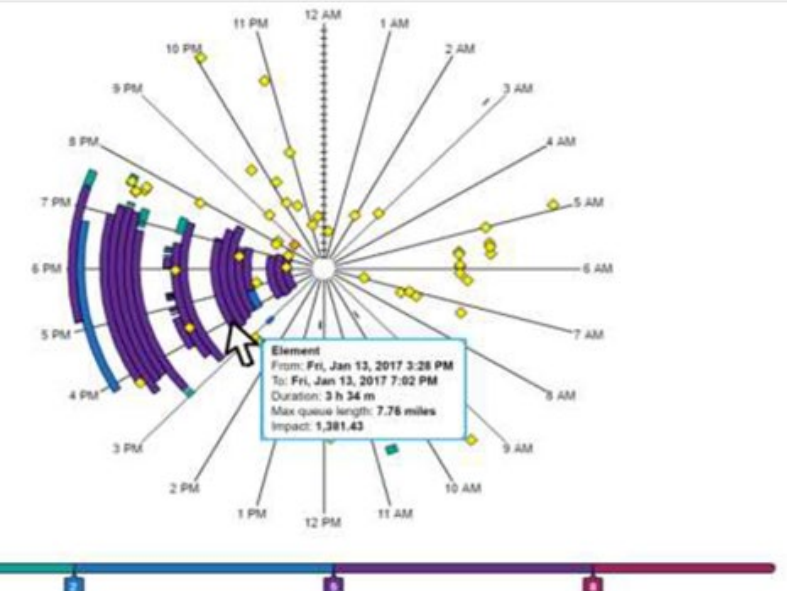


Figure 8. Time Spiral

Source: Franz, M. L., Pack, M. L., Lund, D., & Plaisant, C. (2017). Visualization tools for traffic bottleneck analysis.

Visualization focusing on space & time

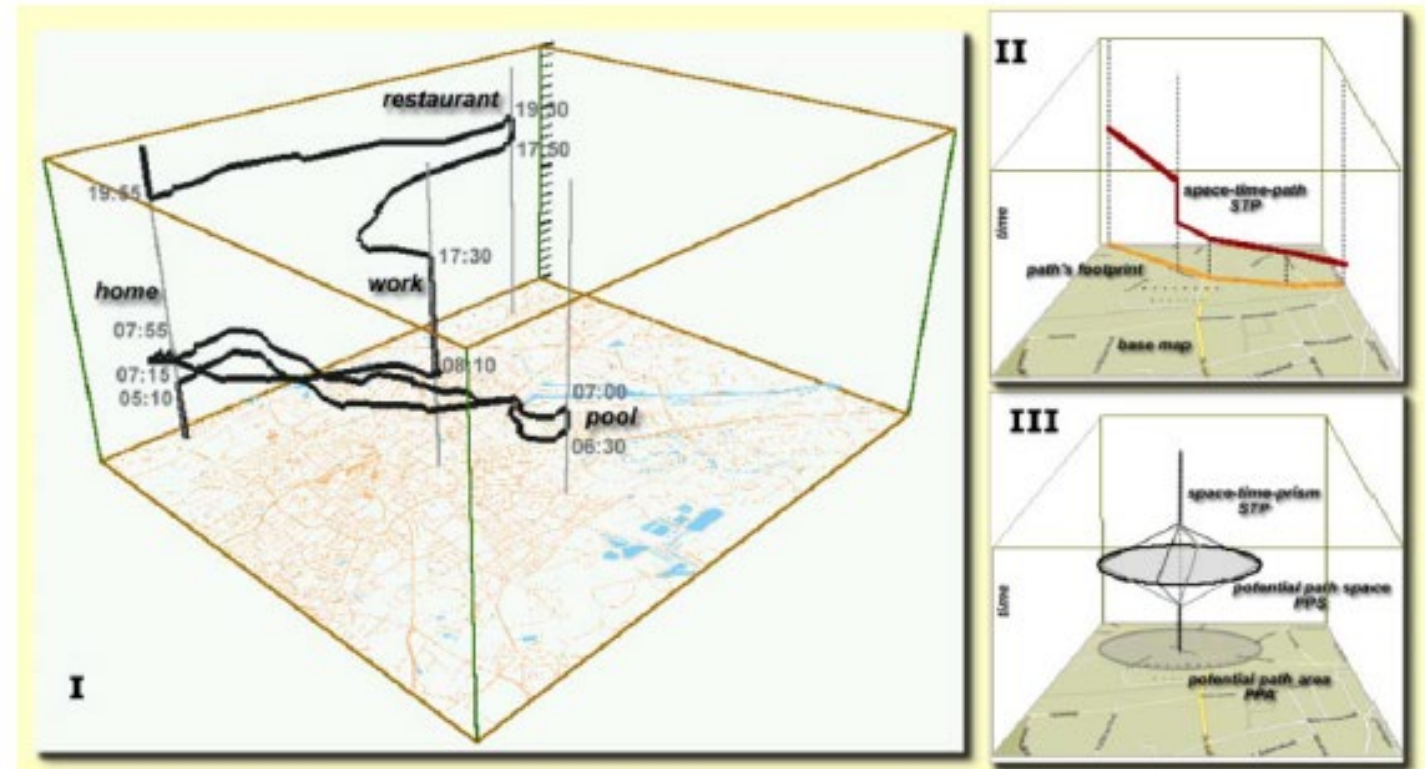


Fig. 12. Space-time-cube: both spatial information and temporal information are visualized in a cube [84]. The X -axis and Y -axis represent spatial information, whereas the Z -axis represents temporal information.

Source: Chen, W., Guo, F., & Wang, F.-Y. (2015). A survey of Traffic Data Visualization.

Visualization focusing on spatial – temporal events



Figure 4

Results of the stop analysis using Flower charts show different patterns of spatiotemporal distribution of stop events.

Source: Bak, P., Ship, H. J., Yaeli, A., Nardi, Y., Packer, E., Saadoun, G., Bnayahu, J., & Peterfreund, L. (2015). Visual analytics for movement behavior in traffic and Transportation.

Hybrid Visualizations

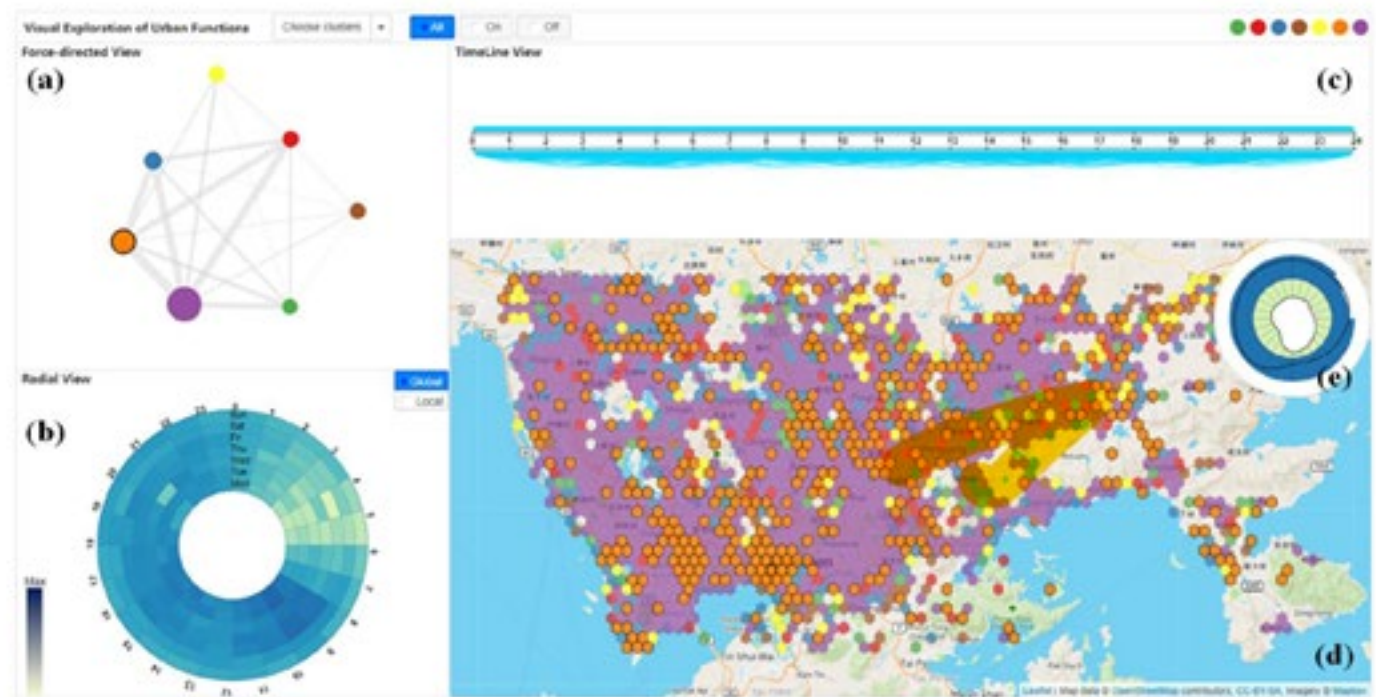


Fig. 1. Visualization for a spatio-temporal taxi OD dataset: (a) a force-directed view to present the correlation between functional areas. (b) a radial view to visualize traffic volume changes over time. (c) a timeline view to present the distribution of pick-up/drop-off and the travel time within or between functional areas. (d) a map view to present global urban functions, in which the temporal distribution of traffic flow volumes of a local area of interest can be checked by means of Glyph designed as shown in (e).

Source: Zhou, Z., Yu, J., Guo, Z., & Liu, Y. (2018). Visual exploration of urban functions via spatio-temporal taxi od data.

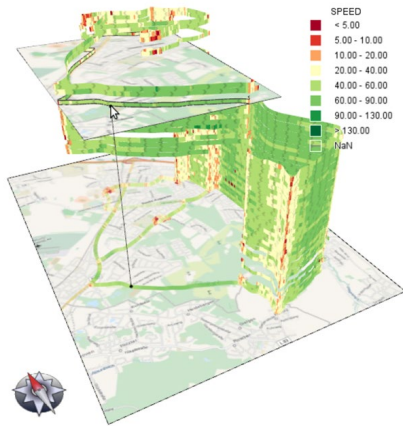


Fig. 4. Visualization of trajectories as colored 3D bands and 2D paths.

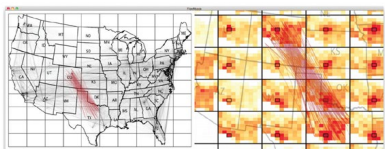


Figure 11. Example of interaction query and linked views. The application shows a flow map view on the left hand side and an ODI map view on the right. Both can be independently zoomed and panned allowing both overview and detail on demand. By brushing over the various quadrants with the South Texas origin cell, the interactions between the locations are overlaid on both views. Trajectories are stored at the resolution of the county centroid.

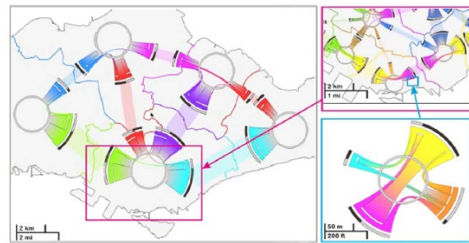


Fig. 11. A region-based visualization example: interchange patterns of metro systems in city scale, regional scale and road network scale [35].



Figure 5. Ohio travel to work flows showing county aliasing. Flows are located at each county's centroid. Where the scale of the county is approximately equal to the scale of the ODI grid, aliasing effects can occur.

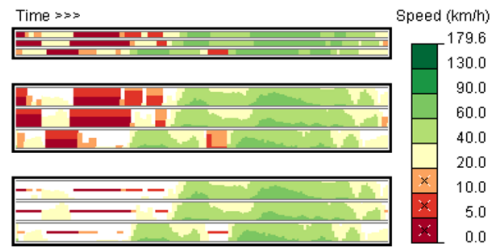


Fig. 2. Alternatives for color-coding attribute values along trajectory bands. Top: plain color-coding requires less space; middle: two-tone pseudo-coloring [30] increases precision; bottom: color filtering reduces visual load.

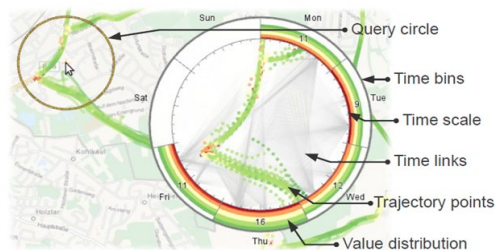


Fig. 5. The time lens visualizes temporally aggregated information.

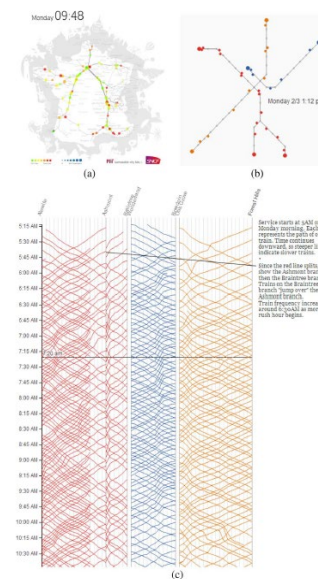


Fig. 5. (a) Train status at 9:48 a.m. in France [20], in which the visualization is based on a railway map and the running trains are labeled by colored points at their locations. (b) and (c) Boston subway status [21] is created based on Boston metro map. (b) the positions of running trains at 1:12 p.m. Monday; (c) an overview of the running status of the metro for one day.

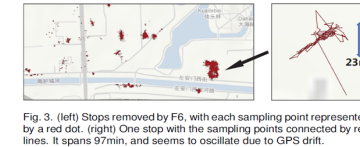


Fig. 3. (left) Stops removed by F6, with each sampling point represented by a red dot. (right) One stop with the sampling points connected by red lines. It spans 97min, and seems to oscillate due to GPS drift.

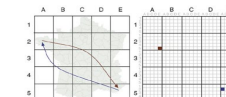


Figure 1. Left: geographic space partitioned into a regular grid. Right: ODI map view. When users use default geobrowsing of geographic space they get lines. Otherwise they control of several modalities of the geographic space (right) grid lines. The red trajectory from geographic location (A,2) to (B,1) is represented by the angle ODI map cell with coordinates (18,2,1). The vector line trajectory is shown as a red line connecting (A,2) to (B,1).

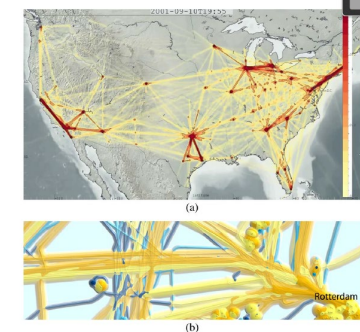
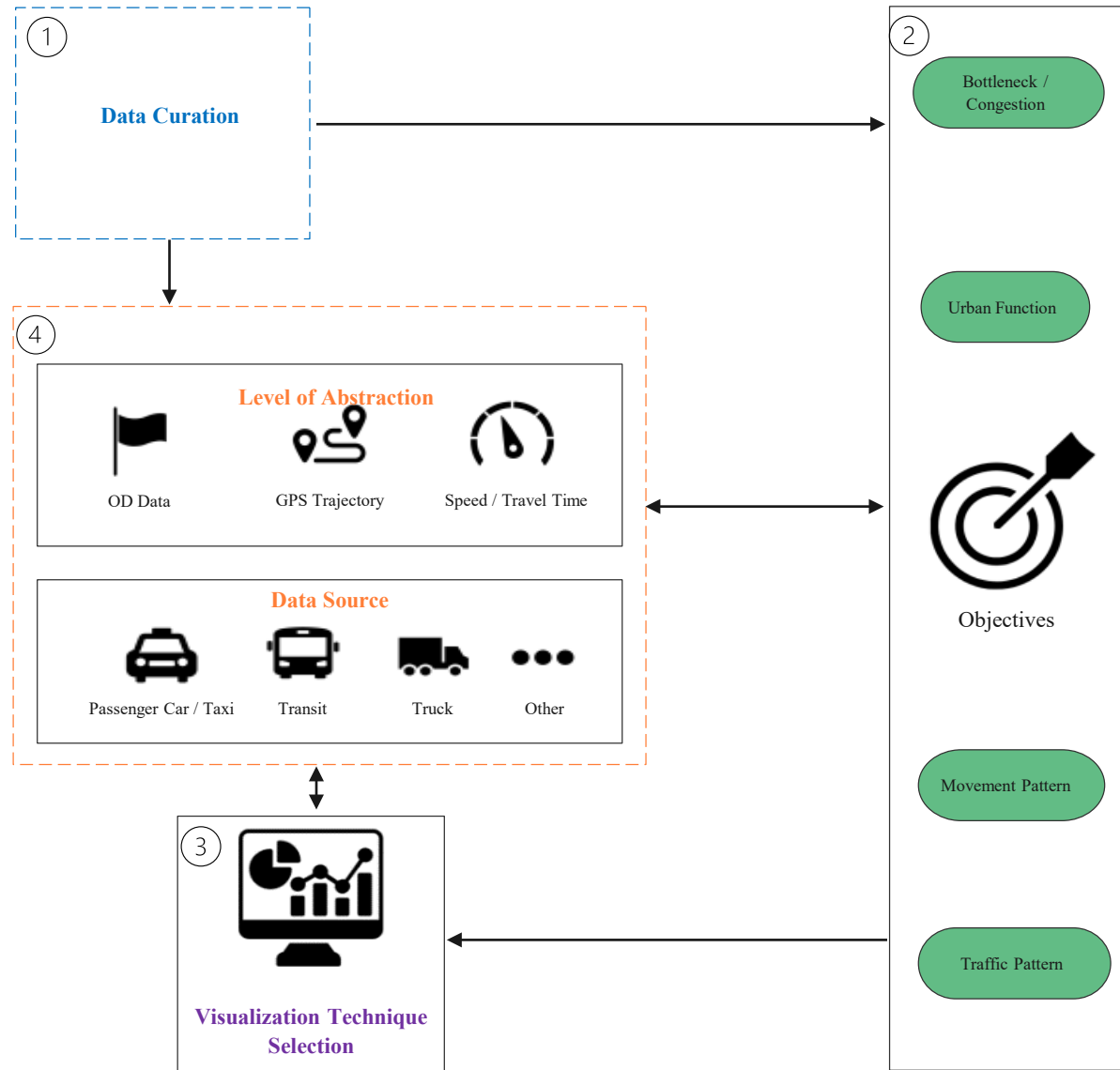


Fig. 10. Densify maps of trajectories: (a) air traffic in the USA [83]; (b) vessel traffic around Rotterdam [4].

There are many more visualizations for telematics

Decision Support Tool



Conclusion

Telematics: Review and Applications in Freight Transportation



Exploit Existing Techniques

Hybrid Visualizations

Data fusion



Thank You

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