Design and Implementation of a Human-Centered Interactive Transportation Dashboard for Small Towns through Heterogeneous Spatial Data Integration

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Abstract. This study focuses on the development of a human-centered interactive transportation dashboard tailored for underserved small towns. By integrating diverse spatial datasets, the dashboard offers a comprehensive understanding of the transportation landscape. The methodology involves the collection of video and audio data related to road conditions in a Texas small town. Geospatial artificial intelligence algorithms process and analyze the data, which is then mapped onto a digital dashboard for intuitive visualization. The dashboard includes trajectory display, selection tools, route length visualization, time nodes, and a bar graph combining time and road segments. These features enable users to easily select and visualize single or multiple trajectories, explore road segment attributes, and access information based on recording time. To sum up, a crowdsourced interactive transportation dashboard plays a crucial role in empowering underserved small towns. It achieves this by facilitating community engagement in data collection, offering real-time information, leveraging local knowledge, and promoting cost-effective solutions. By bridging the gap in technical capacity and data support, it enables the community to actively contribute towards enhancing their transportation systems and improving their overall quality of life.

Keywords: Dashboard, Small Town, Transportation, Crowdsourced, Artificial Intelligence.

1 Introduction

Underserved communities and small towns frequently encounter unique challenges linked to infrastructure, resource accessibility, and socio-economic factors. In recent years, there has been a growing recognition of the significance of developing interactive dashboards that employ heterogeneous datasets. This is particularly crucial in light of the escalating demand to promote community resilience in small towns and underserved communities. The integration of diverse datasets within these dashboards has become increasingly essential to address the unique challenges faced by such communities and to foster their overall resilience. An interactive dashboard has the capability to provide customized solutions to tackle these specific challenges. It serves as a platform for analyzing and comprehending local conditions, enabling the effective implementation of targeted interventions and policies that cater to the distinctive requirements of these communities [1]. This study primarily aims to analyze spatialized video and geo-narratives of roads in Nolanville, a small town in Texas, USA. As a result, a dashboard is developed to offer users a comprehensive understanding of the road network [2]. The Nolanville Dashboard, depicted in Figure 1, incorporates a variety of features, including trajectory display, selection tools, route length visualization, time nodes, and a bar graph integrating time and road segments. These functionalities empower users to select and visualize single or multiple trajectories, view road segment attributes, and access localized or perceived information. The dashboard is meticulously designed with a human-centered approach, prioritizing user-friendliness and intuitive navigation to facilitate seamless data exploration. This paper outlines the methodology employed in creating the dashboard and explores its potential applications in small town transportation management.

Efficient transportation systems are vital for the optimal functioning of underserved communities like Nolanville. With the rise in vehicular traffic, the importance of transportation management has become paramount. Consequently, the development of an interactive transportation dashboard utilizing diverse datasets has become increasingly crucial. This dashboard offers a comprehensive understanding of the road network, enabling policy makers and community leaders to make informed decisions that enhance community travel safety.

The interactive dashboard incorporates a range of powerful features designed to enhance user experience and provide valuable insights. The trajectory display feature offers real-time tracking of vehicles, pedestrians, and cyclists, enabling users to monitor their movements with precision. With the selection tools feature, users can choose specific trajectories or multiple trajectories, gaining access to detailed information about path details and road segment attributes for comprehensive analysis. The route length display feature proves invaluable for trip planning and optimizing travel efficiency, as it provides users with the length of their selected routes. This empowers users to make informed decisions by identifying the shortest route between two points or evaluating distance-based considerations. To facilitate comprehensive analysis of data, the time nodes feature enables users to access information based on the time of capture. This functionality allows users to analyze changes in traffic patterns and road conditions over time, providing valuable insights for decision-making and trend identification. Additionally, the inclusion of a bar graph that combines time with road segments offers users a visual representation of traffic flow and road conditions over time. This graphical representation enhances data interpretation and understanding by showcasing temporal variations and trends, facilitating effective communication and analysis. Collectively, these features empower users with real-time tracking, detailed trajectory selection, route length calculation, temporal analysis, and visual representations, making the interactive dashboard an indispensable tool for monitoring and optimizing transportation systems in small towns and underserved communities.

The dashboard was meticulously crafted with a human-centered approach, prioritizing user-friendliness and intuitive navigation to ensure seamless data exploration. Its user-friendly interface enables transportation managers to swiftly access information, empowering them to make well-informed decisions regarding traffic management. The dashboard's intuitive navigation system further enhances the user experience by enabling effortless exploration of the diverse features and functions, ultimately saving time and increasing overall efficiency.

2 Dashboard overview

To develop an interactive transportation dashboard that provides comprehensive road information, we collect videos and narratives of the road network in Nolanville. The resulting Nolanville Dashboard (refer to Fig. 1) encompasses the following key information:

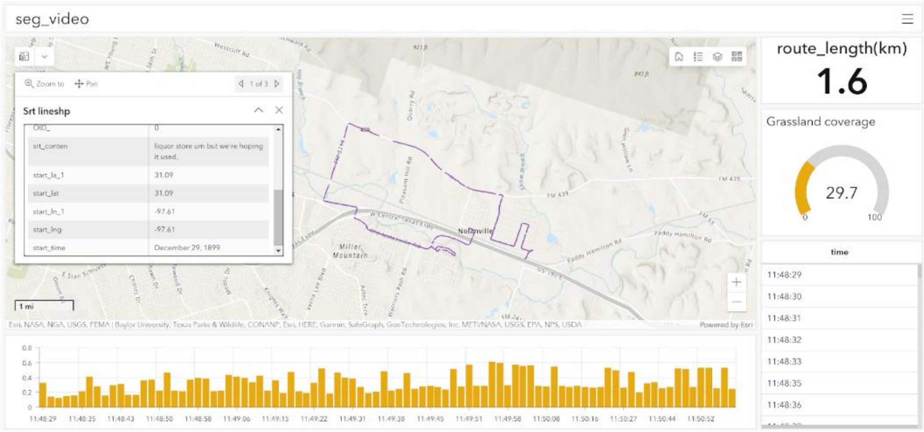

Fig. 1. The interface of our dashboard.

Nolanville Map (center): The purple line represents the trajectory, indicating the location of our video recordings. When users click on a specific segment of the trajectory, a pop-up window displays the corresponding narrative for that particular segment. The base map can be easily switched to satellite images using the option in the top-right corner, providing users with fundamental area information. Additionally, the top-right corner features tools to show the legend, allowing users to differentiate the trajectory and navigate back to the home page, among other options.

Situated on the top-left corner of the Dashboard is the selection tool, which empowers users to choose one or multiple trajectories. This tool facilitates the customization of the displayed data according to the specific trajectories of interest, allowing users to focus on the information that is most relevant to their analysis or exploration.

A pie chart: This feature provides valuable information such as the percentage of buildings, green space, water, and other relevant attributes. By visualizing these attributes, users can gain insights into the composition and characteristics of the road sections, enabling them to make informed decisions or observations based on the specific attributes of interest.

Route length display (top-right of the dashboard): This feature dynamically calculates and presents the total length of the current route displayed on the screen. As users navigate through the map, the route length is automatically recalculated, providing real-time updates and ensuring accurate information regarding the length of the selected route. This feature proves particularly useful for trip planning, as users can easily determine the distance of their chosen route and make informed decisions based on this information.

Time nodes (bottom-right of the dashboard): To access information based on the recording time, users can simply select the corresponding road segment on the dashboard. By clicking on a specific road segment, users can retrieve relevant information that corresponds to the time of recording. This functionality allows for a temporal analysis of the data, enabling users to understand how road conditions or other attributes may have varied over different recording periods. It provides a valuable tool for studying temporal patterns and making data-driven assessments based on the specific timeframes of interest.

A bar graph (right-middle of the dashboard): Incorporating the time element with the road segments, the dashboard visualizes the relationship between time and the attributes of the road network. One notable representation is the depiction of the amount of green space captured in the video within the current view. This feature enables users to gain insights into the presence and distribution of green spaces along the road segments over time. By combining temporal information with the road network, users can analyze the dynamics of green spaces and their potential impact on the overall environment.

3 Data collection

All the data utilized in our Dashboard was collected by our team in Nolanville, Texas, USA, through a car-mounted camera. Nolanville is a small city situated in Bell County, Texas. The data collection process involved driving the car at a speed of 30 miles per hour while recording videos, audio, and the vehicle's current position using a specialized device. We obtained two 30-minute-long videos that captured the road and the surrounding landscape during the journey. Additionally, we recorded voice files providing descriptions of the road, allowing for the analysis of various emotional reactions experienced while driving along the route. The coordinates file obtained during the drive serves as the foundation for our map, displaying the latitude and longitude as we progressed.

4 Methodology

The development and testing of the dashboard were conducted on a personal laptop with the following specifications: AMD 4600H processor, NVIDIA GTX 1650 graphics card, 16GB RAM, and a 512GB SSD storage. The laptop provides sufficient computing power to process the video and audio data effectively. Regarding the processing of the data, the following steps were undertaken:

4.1 Video Processing

To extract the street image information corresponding to each point from the video, we employ a frame extraction process. The video is converted into individual images, with a frame rate of 30 frames per second (fps). This allows us to obtain a series of split images that were sorted according to their respective timestamps. By converting the video into images at a consistent frame rate, we can preserve the temporal information associated with each frame. This enables us to accurately link the extracted images to the specific points in time during the movement captured in the video. The resulting split images, sorted chronologically, serves as the basis for further analysis and mapping on the dashboard. They provide a visual representation of the street views corresponding to each point in time, facilitating a detailed examination of the road network and surrounding environment.

Semantic Segmentation. We use semantic segmentation to extract the required information from images. Semantic segmentation is a deep learning-based full convolutional network (FCN) called FCN-8s [1]. Convnets are inherently translation invariant, meaning that they operate on local input regions and depend only on relative spatial coordinates. This makes them well-suited for semantic segmentation, as they can identify objects in images regardless of their position or orientation. Writing x_{ij} for the data vector at location (i, j) in a particular layer, and y_{ij} for the following layer, these functions compute outputs y_{ij} by

$$y_{ij} = f_{ks}\left(X_{si+\delta i, sj+\delta j}{}_{0\le\delta i,\delta j<k}\right) \tag{1}$$

where k is the kernel size, s is the stride or subsampling factor, and f_{ks} determines the layer type: a matrix multiplication for convolution or average pooling, a spatial max for max pooling, or an elementwise nonlinearity for an activation function, and so on for other types of layers.

This functional form is maintained under composition, with kernel size and stride obeying the transformation rule:

$$f_{ks} \circ g_{k's'} = (f \circ g)_{k'+(k-1)s',ss'} \tag{2}$$

A standard neural network computes a general nonlinear function, but a network composed solely of layers with convolutional operations performs a specific type of computation known as a nonlinear filter. This specialized network, also referred to as a deep filter or fully convolutional network (FCN), is capable of processing inputs of any size and generating outputs with corresponding spatial dimensions, which may be resampled if needed. The inherent nature of an FCN allows it to efficiently operate on a wide range of input data while preserving spatial information.

The images obtained from the dataset are classified into several categories, including sky, grass, ground, trees, buildings, and roads. The network achieves a pixel contrast accuracy of 0.814426 on the training dataset and 0.66839 on the test dataset. The processed results consist of both classified images and corresponding data tables.

Classified Images into Video. The classified images are transformed into grayscale maps, where each pixel is assigned a category number representing a specific class. For example, if buildings are designated as the second category, the pixel value within the segmented building area is set to 2. This mapping is applied to all other categories accordingly. The classified images are subsequently converted back into a video format with a frame rate of 30 frames per second (fps), resulting in a semantic segmentation classification video.

Georeferencing the results. The segmented data obtained from the images is stored in a CSV file, which contains the feature percentage and corresponding category for each image. To establish a connection between the timestamps in the images and their corresponding geographic coordinates, we leverage the coordinate file. Given that the frame rate is 30 frames per second (fps), each set of 30 images shares the same time point and coordinates. Consequently, we calculate the average feature percentage for each coordinate point within the same second. This process yields the street view classification results for the video, encompassing latitude, longitude, and feature percentages. By plotting these coordinate points on a map, we can effectively visualize our route, incorporating the street view classification outcomes.

4.2 Audio Processing

During the video recording, the environment is described, providing valuable insights and context. These descriptions encompass various aspects, including personal feelings about the surroundings (e.g., the neighborhood being safe) and historical information about points of interest (e.g., a closed drug store). To extract the subtitles from the voice file, we utilize a voice-to-text service provided by Google Cloud, which generates a subtitle file with timestamps. Each sentence in the subtitle file lasts approximately 5 to 10 seconds. Additionally, we employ topic modeling techniques to categorize the narrative into different topics. By visualizing the narrative sorted by topics, users can easily focus on the content that interests them the most.

Preprocess the subtitles: The initial stage in preparing the subtitles for topic modeling is the preprocessing step. During this phase, the text is subjected to various cleaning and normalization procedures to ensure optimal results. Common preprocessing techniques include converting all words to lowercase and eliminating stop words, such as "the," "a," and "an." By performing these

operations, the text is streamlined and irrelevant elements are removed, allowing for more accurate topic modeling outcomes.
Create a document-term matrix: This step involves creating a document-term matrix that captures the term frequencies within each subtitle. For this purpose, we utilize the CountVectorizer from the scikit-learn library [2]. The document-term matrix provides a numerical representation of the text data, where rows correspond to subtitles and columns represent individual terms. By employing CountVectorizer, we can transform the textual information into a structured format suitable for further analysis and modeling.
Topic Modeling: Topic modeling algorithms, such as Latent Dirichlet Allocation (LDA) and Non-Negative Matrix Factorization (NMF), are commonly employed for extracting topics from textual data. In this study, we utilize LDA as it is widely recognized and widely used in the field of topic modeling [3-5]. After data preparation and algorithm selection, the model is trained on the document-term matrix, enabling the identification of the prominent topics present within the subtitles. By leveraging LDA, we are able to uncover and analyze the underlying themes and subjects embedded within the narrative data.
Evaluate and interpret the results: Following the training of the model, we conduct an evaluation to assess the model's performance in identifying the main topics within the subtitles. This evaluation helps us understand the nature and representation of each topic. One important aspect to highlight is that topic modeling is an unsupervised learning technique, meaning that it does not require labeled data for training. This makes it particularly valuable for analyzing text data that lacks manual labeling or annotation, as is often the case with small towns where resources for data labeling are limited. The unsupervised nature of topic modeling enables efficient analysis and extraction of meaningful insights from unlabeled text data.

4.3 Plotting on the map

Visualizing this information on the dashboard brings the map to life and provides users with a comprehensive view of the environment. To achieve this, we need to establish the correspondence between the text results and the coordinate points based on the timeline information. This involves mapping the timeline information to the time points in the video and then linking it to the coordinate file. By doing so, we are able to match the narrative with the vehicle trajectory and align it with specific line segments on the road.

To visualize the processed video and its georeferenced results, we utilize the ArcGIS dashboard [6]. The segmented videos and audios are represented as line features on the map. Finally, the route described in the voice file is drawn on the map, segment by segment, creating a comprehensive representation of the narrative along the route.

5 Conclusion

This paper presents the development of a human-centered interactive transportation dashboard tailored for small towns. By leveraging heterogeneous datasets and utilizing AI techniques, we collected video and audio data of roads in Nolanville, Texas, and processed the information to create an informative and user-friendly dashboard [7]. The dashboard provides users with enhanced road information, navigation tools, and visualizations, enabling improved transportation management and informed decision-making. The successful implementation of our approach highlights the potential of AI and video data in developing interactive transportation dashboards for small towns and lays the groundwork for further advancements in data-driven transportation solutions [8]. This research contributes to the field by showcasing the benefits of such dashboards and sets the stage for future studies in this area, both in small towns and larger cities [9].

The Nolanville Dashboard holds immense potential for various applications, particularly in the domain of small-town transportation management. By offering transportation managers a comprehensive understanding of traffic flow and real-time road conditions, the dashboard becomes a valuable tool for making informed decisions. Its application can range from optimizing traffic management strategies and reducing the occurrence of traffic accidents to enhancing overall transportation efficiency within the community. With its ability to provide up-to-date and detailed information, the dashboard empowers transportation managers to proactively address transportation challenges and contribute to safer and more efficient transportation systems in small towns.

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References

1. Du, J., Ye, X., Newman, G., & Retchless, D. (2022, November). Network science-based urban forecast dashboard. In Proceedings of the 5th ACM SIGSPATIAL International Workshop on Advances in Resilient and Intelligent Cities (pp. 7-10).

2. Jamonnak, S., Bhati, D., Amiruzzaman, M., Zhao, Y., Ye, X., & Curtis, A. (2022). VisualCommunity: a platform for archiving and studying communities. Journal of Computational Social Science, 5(2), 1257-1279.
3. Helbich, M., Yao, Y., Liu, Y., Zhang, J., Liu, P., & Wang, R. (2019). Using deep learning to examine street view green and blue spaces and their associations with geriatric depression in Beijing, China. *Environment International*, *126*, 107–117. https://doi.org/10.1016/j.envint.2019.02.013
4. Hoffman, M., Bach, F., & Blei, D. (2010). Online learning for latent dirichlet allocation. advances in neural information processing systems, 23.
5. Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, *3*(Jan), 993–1022.
6. Newman, G., Malecha, M., & Atoba, K. (2021). Integrating ToxPi outputs with ArcGIS Dashboards to identify neighborhood threat levels of contaminant transferal during flood events. Journal of Spatial Science, 1-13.
7. Jamonnak, S., Zhao, Y., Curtis, A., Al-Dohuki, S., Ye, X., Kamw, F., & Yang, J. (2020). GeoVisuals: a visual analytics approach to leverage the potential of spatial videos and associated geonarratives. International Journal of Geographical Information Science, 34(11), 2115-2135.
8. Huang, X., Zhao, Y., Ma, C., Yang, J., Ye, X., & Zhang, C. (2015). TrajGraph: A graph-based visual analytics approach to studying urban network centralities using taxi trajectory data. IEEE transactions on visualization and computer graphics, 22(1), 160-169.
9. Ye, X., Du, J., Han, Y., Newman, G., Retchless, D., Zou, L., ... & Cai, Z. (2023). Developing human-centered urban digital twins for community infrastructure resilience: A research agenda. Journal of Planning Literature, 38(2), 187-199.