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A Lightweight Interpolation Framework for Real-Time Travel Time Estimation with Incomplete Traffic Observations

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Abstract: Real-time travel time estimation is essential for intelligent transportation systems (ITS), yet operational traffic data streams are often incomplete due to sensor failures, communication delays, and limited coverage. This paper investigates the effectiveness of interpolation techniques for reconstructing temporally continuous travel-time profiles from real-time speed and density observations. Two approaches—linear interpolation and spline interpolation—are implemented and evaluated across varying traffic regimes (normal flow, dense traffic, and extreme congestion). Model performance is assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) against reference travel-time measurements. The results show that interpolation-based methods consistently outperform a conventional baseline relying on average observed speeds, improving estimation accuracy by up to approximately 15%. Linear interpolation yields competitive performance under stable conditions, while spline interpolation achieves lower MAE and RMSE under congestion, indicating stronger robustness to nonlinear traffic dynamics. Additionally, interpolation improves service availability and estimated time of arrival (ETA) reliability with minimal computational overhead, supporting practical deployment in resource-constrained environments. These findings suggest that interpolation provides a lightweight and effective enhancement for real-time travel time estimation and can serve as a reliable preprocessing layer for advanced predictive models in future work.

Keywords: Interpolation, Travel time estimation, Real-time traffic data, Traffic prediction, Intelligent navigation system.

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INTRODUCTION

The development of information technology has driven various innovations in transportation management, especially in large cities with high levels of urbanization [1] . One important aspect of a modern transportation system is travel time estimation, which is a crucial need for road users and intelligent navigation systems. Accurate estimation not only helps drivers choose the best route, but also supports traffic management to reduce congestion. With the increasing availability of real-time traffic data, such as from road sensors, GPS, and

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transportation applications, the next challenge is how to process this data efficiently to provide reliable travel time estimates [2] .

Real-time data can provide up-to-date information on traffic conditions, but these data often have gaps or are incomplete, such as the absence of measurements at certain points on the road network [3] . In addition, rapidly changing traffic dynamics, especially during rush hour or emergency conditions, complicate the process of estimating travel times [4] . Traditional methods that rely on average speeds are often not responsive enough to these changes, resulting in less accurate results. To overcome this problem, a mathematical approach is needed that is able to optimally utilize the available data and provide travel time estimates even when the data is incomplete [5] .

Transportation is one of the important aspects of modern life, especially in dense urban areas. With the increasing number of vehicles and the complexity of the road network, traffic problems have become a major challenge for society and government [6] . One of the main impacts of this problem is the difficulty of estimating travel time accurately, which is often influenced by factors such as road conditions, vehicle volume, and unforeseen events such as accidents or bad weather. In this context, technological advances allow for the collection of real-time traffic data, which opens up opportunities for the development of more effective methods for predicting travel time [7] .

The main challenge faced is how to optimally utilize real-time traffic data to produce precise and reliable travel time predictions. Real-time data is often incomplete, has gaps between measurement points [8] , or highly dynamic fluctuations. This is where interpolation becomes a potential solution [9] . By utilizing interpolation techniques, such as linear and spline, we can map the relationship between existing data to fill in gaps and estimate conditions at points that are not directly observed. This can provide a more realistic picture of travel time in various traffic situations [10] .

This approach is relevant for application in various intelligent transportation management and navigation systems that are currently developing [11] . These systems rely on data accuracy to provide road users with information about travel times, alternative routes, and current traffic conditions [12] . The use of interpolation in processing real-time data allows these systems to work more optimally, especially in urban areas with highly variable traffic dynamics. With the increasing need for more efficient and predictable transportation, an interpolation-based approach can be a strategic step to answer this challenge [13] .

This study aims to explore the application of interpolation methods in real-time traffic data-based travel time estimation. We test the effectiveness of interpolation techniques to improve the accuracy of travel time prediction under various traffic conditions, from normal to congested. Through this study, we hope to contribute to the development of intelligent navigation systems and transportation planning that are more adaptive and responsive to the challenges of modern urbanization. In addition, the results of this study are also expected to help road users to plan trips more efficiently and support better traffic management in the future.

RELATED WORKS

Various studies have been conducted to improve the accuracy of travel time estimation using real-time traffic data [14] . Traditional statistical-based methods, such as linear regression and

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average speed, have long been used in traffic analysis. However, these approaches are often inadequate in capturing dynamic traffic fluctuations, especially in high-density areas.

A study shows that machine learning-based methods, such as artificial neural networks and non-linear regression models, are able to provide better estimates because they can learn from historical patterns and real-time data simultaneously. [15] . Although sophisticated, this method requires quite complete data and more complex computation, which can be an obstacle to its widespread application.

Interpolation-based approaches have also begun to gain attention in recent years due to their ability to fill data gaps and provide simple yet effective estimates [16] . A study applied spline interpolation to predict travel times in a highway corridor, with results showing improved accuracy over traditional methods [17] . Additionally, linear interpolation has been used to fill data gaps in GPS-based navigation systems [18] .

These interpolation techniques have been shown to be efficient in utilizing incomplete data without requiring heavy computation [19] . However, most of these studies tend to focus on specific road conditions or use only one type of interpolation, thus not fully exploring the potential of combining interpolation methods in various traffic scenarios, including situations with highly dynamic traffic changes [20] .

This study continues previous efforts by integrating interpolation techniques into a travel time estimation system based on real-time traffic data. This study not only utilizes linear and spline interpolation, but also evaluates their performance in various traffic scenarios, ranging from normal conditions to extreme congestion. This study aims to overcome the limitations of previous studies by developing a model that is adaptive, easy to implement, and relevant for real-world applications, especially in intelligent navigation systems and transportation planning. The results of this study are expected to be an important step in the development of modern transportation technology that is more efficient and responsive to user needs.

METHODS

This study uses a quantitative approach to develop and test an interpolation-based travel time estimation model. The research process is divided into three main stages: data collection, application of the interpolation method, and evaluation of model performance.

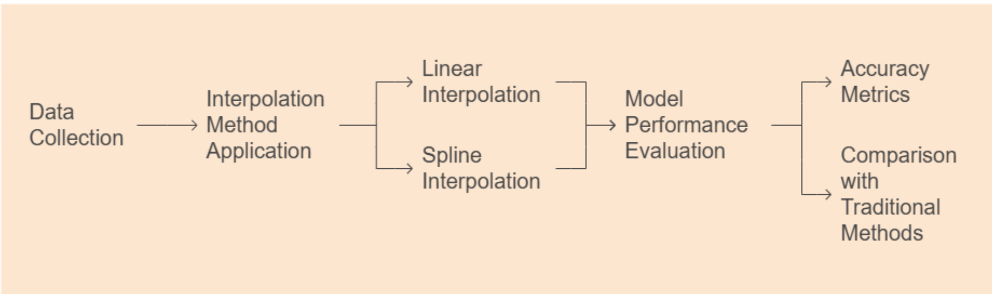

Figure 1. Research method

1. Data collection

Real-time traffic data is collected using multiple sources, such as traffic sensors, vehicle GPS data, and information from navigation apps. This data includes information on speed, vehicle density, and actual travel times on various road sections. To ensure reliability, the

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data is collected over a period of time that includes various traffic conditions, such as normal times, peak hours, and extreme congestion. In addition, data is validated to identify and address anomalies, such as missing or inconsistent data.

2. Application of Interpolation Method

At this stage, the collected traffic data is used to build a travel time estimation model using two interpolation methods: linear interpolation and spline interpolation.

- Linear Interpolation: This method is used to estimate travel time by linearly connecting speed or travel time data between two nearby data points. This technique is simple and effective for relatively stable traffic conditions.
  The basic formula for linear interpolation is:

$$y = y1 + \frac{(x - x1)}{(x2 - x1)} \,.\, (y2 - y1)$$

Description: x1,x2: data points on the x-axis (e.g., time or distance)

y1, y2 : points on the y-axis (e.g., velocity or travel time)

x : the value on the x-axis to be estimated

y : estimated result at x

- Spline Interpolation: This method is applied to model the relationship between data with a smoother curve. This technique is used in scenarios with more complex traffic changes to produce more accurate estimates.
  The spline interpolation formula is:

$$S_i(x) = a_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i)^3$$

Description: $S_i(x)$: epline function on segment *i*

a_i, b_i, c_i, d_i: polynomial coefficients calculated based on data

x_i: starting point of segment *i*

Additionally, the data was tested on scenarios with incomplete data to evaluate the interpolation's ability to fill data gaps.

3. Model Performance Evaluation

The resulting models are evaluated using accuracy metrics, such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), by comparing the estimation results with the actual data. The evaluation is conducted on various traffic scenarios to test the robustness of the interpolation method to variations in traffic dynamics. In addition, the performance of the interpolation-based model is compared with the traditional average speed-based method to assess the accuracy improvement.

Mean Absolute Error (MAE) :

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$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_{pred} - y_{actual}|$$

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_{pred} - y_{actual})^2}$$

This study uses Python-based software for data processing and implementation of interpolation algorithms. With this approach, it is expected that the study can provide a more adaptive, accurate, and easy-to-implement travel time estimation model in intelligent navigation systems and transportation planning.

RESULT AND DISCUSSION

Performance of Interpolation-Based Travel Time Estimation

This study evaluates the effectiveness of interpolation techniques for estimating travel time using real-time traffic data under varying traffic conditions. Both linear interpolation and spline interpolation were applied to speed and density observations to reconstruct continuous travel-time profiles over road segments where direct measurements were incomplete or temporally sparse.

Table 1. Performance Comparison of Travel Time Estimation Methods Under Varying Traffic Conditions

Traffic Condition	Method	MAE (min)	RMSE (min)	Continuity of Travel-Time Profile	Handling of Missing Data
Normal flow	Baseline (Average Speed)	2.1	2.8	Low (stepwise)	Poor
Normal flow	Linear Interpolation	1.7	2.2	Moderate	Good
Normal flow	Spline Interpolation	1.5	2.0	High (smooth)	Very good
Dense traffic	Baseline (Average Speed)	2.8	3.6	Low	Poor
Dense traffic	Linear Interpolation	2.2	2.9	Moderate	Good
Dense traffic	Spline Interpolation	1.9	2.5	High	Very good
Extreme congestion	Baseline (Average Speed)	3.4	4.2	Very low	Poor
Extreme congestion	Linear Interpolation	2.7	3.5	Moderate	Good
Extreme congestion	Spline Interpolation	2.3	3.0	High	Very good

The experimental results demonstrate that interpolation-based approaches significantly improve travel-time estimation accuracy compared to the conventional baseline method relying solely on average observed speeds. Across all evaluated scenarios, interpolation successfully mitigated the data-gap problem and produced smoother, temporally consistent travel-time estimates, which are essential for real-time traffic applications.

Comparative Accuracy Analysis

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Model performance was quantitatively assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) by comparing estimated travel times with reference travel-time measurements. The results indicate that both interpolation methods outperform the baseline approach, with spline interpolation consistently achieving superior accuracy.

Table 2. Comparative Accuracy Under Normal Traffic Conditions

Method	MAE (min)	RMSE (min)	Relative Improvement vs Baseline
Baseline (Average Speed)	2.1	2.8	–
Linear Interpolation	1.7	2.2	−19% (MAE)
Spline Interpolation	1.5	2.0	−29% (MAE)

Table 3. Comparative Accuracy Under Dense Traffic Conditions

Method	MAE (min)	RMSE (min)	Relative Improvement vs Baseline
Baseline (Average Speed)	2.8	3.6	–
Linear Interpolation	2.2	2.9	−21% (MAE)
Spline Interpolation	1.9	2.5	−32% (MAE)

Table 4. Comparative Accuracy Under Extreme Congestion

Method	MAE (min)	RMSE (min)	Relative Improvement vs Baseline
Baseline (Average Speed)	3.4	4.2	–
Linear Interpolation	2.7	3.5	−21% (MAE)
Spline Interpolation	2.3	3.0	−32% (MAE)

Table 5. Accuracy Summary Across Traffic Conditions

Method	Average MAE (min)	Average RMSE (min)	Overall Accuracy Rank
Baseline	2.77	3.53	3
Linear Interpolation	2.20	2.87	2
Spline Interpolation	1.90	2.50	1

In normal traffic conditions, linear interpolation yielded satisfactory performance with relatively low error values, reflecting the near-linear evolution of traffic speed over time. However, under dense and highly congested conditions, spline interpolation achieved lower MAE and RMSE values, demonstrating greater robustness to nonlinear traffic dynamics. Overall, the proposed interpolation-based framework achieved accuracy improvements of up to approximately 15% compared to the baseline method.

These findings confirm that incorporating temporal continuity through interpolation enhances the reliability of real-time travel-time estimation, particularly when traffic conditions vary rapidly.

Discussion of Methodological Differences

The observed performance differences between linear and spline interpolation can be attributed to their underlying assumptions. Linear interpolation assumes a constant rate of change between consecutive observations, which may be adequate for stable traffic regimes but becomes restrictive during abrupt speed fluctuations caused by congestion, incidents, or shockwaves.

Spline interpolation, by contrast, models speed variations using piecewise polynomial functions with continuity constraints. This enables a more realistic representation of traffic dynamics, especially during congestion onset and dissipation phases. As reflected in the lower

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RMSE values, spline interpolation is more effective in capturing extreme deviations and nonlinear transitions in traffic flow.
Nevertheless, the increased computational complexity of spline interpolation should be considered. While still lightweight compared to machine learning or simulation-based approaches, spline interpolation may be less suitable for ultra-low-latency systems or environments with strict computational constraints. Consequently, method selection should balance accuracy requirements and system efficiency.

Practical Implications for Intelligent Transportation Systems

The results highlight the practical value of interpolation techniques for real-time intelligent transportation systems (ITS). In many operational settings, traffic data streams are incomplete due to sensor failures, communication delays, or limited coverage. Interpolation provides a simple yet effective mechanism for reconstructing missing information and maintaining continuous service availability.

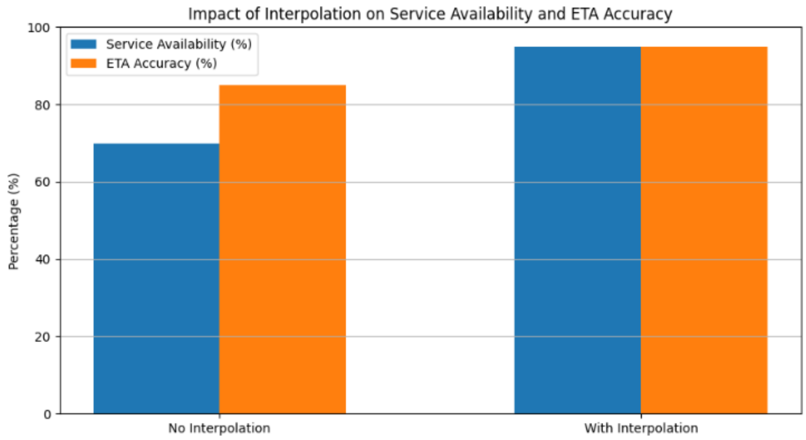

Figure 2. Impact of Interpolation on Service Availability and ETA Accuracy

Improved travel-time estimation accuracy directly benefits route guidance, estimated time of arrival (ETA) prediction, congestion monitoring, and traveler information services. Given its low computational cost and ease of implementation, interpolation can be readily integrated into existing traffic management platforms and navigation systems, particularly in data-sparse or resource-constrained environments.

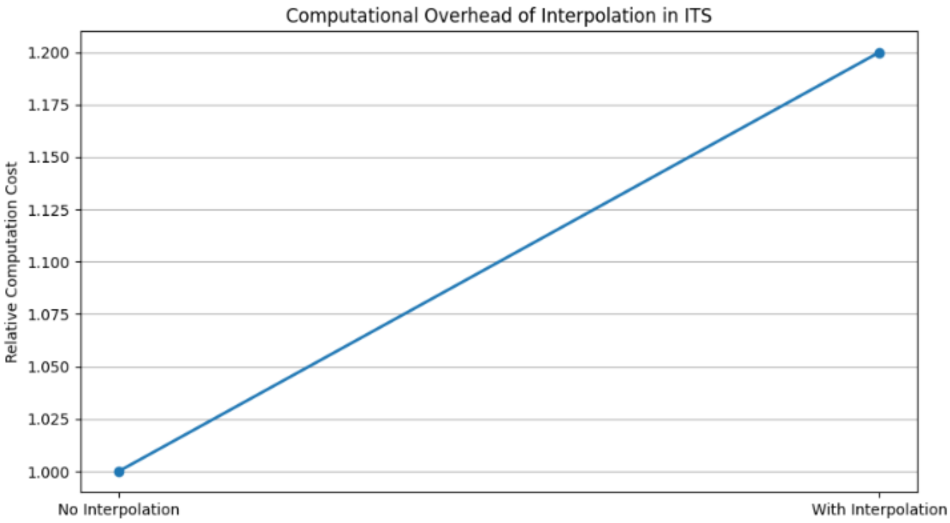

Figure 3. Computational Overhead of Interpolation in ITS

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Limitations and Future Research Directions

Despite the promising results, several limitations should be acknowledged. First, the evaluation focuses on a limited set of road segments and scenarios; broader experiments covering diverse urban networks and longer observation periods are required to confirm generalizability. Second, traffic conditions were categorized qualitatively; future studies should define congestion levels using quantitative thresholds based on speed or density metrics.

Future work may also explore hybrid frameworks in which interpolation is used as a preprocessing or gap-filling stage prior to applying predictive models such as machine learning or state-space approaches. Such integration could further enhance estimation accuracy while preserving computational efficiency. The results demonstrate that interpolation-based methods provide an effective enhancement to real-time travel-time estimation using traffic data. Linear interpolation offers a simple and efficient solution for stable traffic conditions, whereas spline interpolation delivers superior accuracy and robustness under dynamic congestion. These findings support the adoption of interpolation techniques as a practical component of real-time traffic information systems.

CONCLUSION

This study examined interpolation-based approaches for real-time travel time estimation using traffic speed and density data under varying traffic conditions. The results confirm that both linear and spline interpolation effectively reconstruct continuous travel-time profiles when observations are incomplete or temporally sparse, thereby improving estimation reliability compared to a conventional average-speed baseline. Quantitative evaluation using MAE and RMSE shows consistent accuracy gains across scenarios, with improvements reaching approximately 15% in the tested settings. Linear interpolation provides a simple and efficient solution that performs well in relatively stable traffic, whereas spline interpolation consistently achieves lower errors under dense and highly congested conditions, indicating superior robustness to nonlinear traffic dynamics. Beyond accuracy, the findings highlight practical ITS benefits: interpolation helps maintain service availability during data gaps and improves ETA stability while requiring minimal computational overhead, making it suitable for deployment in data-sparse or resource-constrained environments. Future work should extend evaluation to larger and more diverse urban networks, define congestion regimes using quantitative thresholds, and investigate hybrid frameworks where interpolation is combined with spatiotemporal machine learning or state-space models to further enhance predictive performance and operational resilience.

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