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Comparison of Geometric-based Travel Time Prediction between Cars and Trucks

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ABSTRACT

Travel time can be estimated using various approaches, such as historical data, traffic data, machine learning, and road geometry. In this paper, our focus is on prediction based on road geometry. By utilizing the curvature data of a road computed from GPS data, it is possible to determine the design speed of a specific road section. This information can then be used to estimate the time it would take to travel that particular stretch of road. For this paper, we test the algorithm on a 1.7km road in Kulim, Kedah, and observe its reliability of prediction for cars and trucks. While it provides accurate predictions for cars, it produces higher errors for trucks, implying that the approach is more suitable for cars than heavier vehicles. Insights gained from this research can inform future efforts to refine prediction models and enhance the accuracy and reliability of travel time estimation based on road geometry, especially for heavy vehicles.

1. Introduction

In today's fast-paced world, accurate travel time prediction plays a crucial role in improving transportation efficiency and enhancing the overall travel experience for individuals. Whether it is for daily commuting, planning trips, or optimizing logistics operations, having reliable information about travel time can significantly impact decision-making processes. Over the years, various approaches have been developed to tackle this challenge, utilizing a wide range of data sources and analytical techniques.

For example, to get from Point A to Point B, we can casually search on Google Maps or Waze to obtain the estimated travel time. Travel time estimation or can also interchangeably used as travel time prediction is widely used in travelling planning. Other than personal journey or commuting to work, some people rely on travel time prediction to wait for e-hailing, buses or delivery services.

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There are various ways to estimate travel time such as using historical data [1-3], traffic data [4-7], machine learning [8-10] and road geometry [11]. In many modern navigation systems, all types of data are used together [12].

Although there are numerous studies that estimate travel time predictions, these predictions are generally more applicable to car drives rather than heavy vehicles like trucks. However, there are few research that focuses on travel time predictions for trucks.

To build a travel time prediction model, Cheng *et al.,* [13] define 3 specific expected speed for car, truck and bus in their calculation. Wang *et al.,* [14] predicts freeway truck travel time by using empirical truck probe GPS data and loop detector data. Karimpour *et al.,* [15] imputes the common missing values in the usually low sampling rate of truck travel time by using statistical learning and interpolation. Duvvuri *et al.,* [16] combined historical data for truck travel time with road characteristics (such as number of lanes) and on-network characteristics (such as peak hours for the road) to investigate the association between truck travel time performance.

In this paper, we extend the work of Ramli *et al.,* [17] which predicts travel time based on road geometry. The approach in the paper uses the curvature information of a road to derive the design speed to approximate the driving time for the section of the road and we will briefly discuss this in the next section.

We are interested in seeing the result it has on cars and trucks. We are also desire to incorporate a delay factor for trucks in travel time predictions in comparison to cars. In the methodology, we discuss our experiment setting on a 1.7 km road in Kulim, Kedah. Then we will observe its reliability of prediction on cars and trucks.

2. Procedure for Geometric-Based Travel Time Prediction

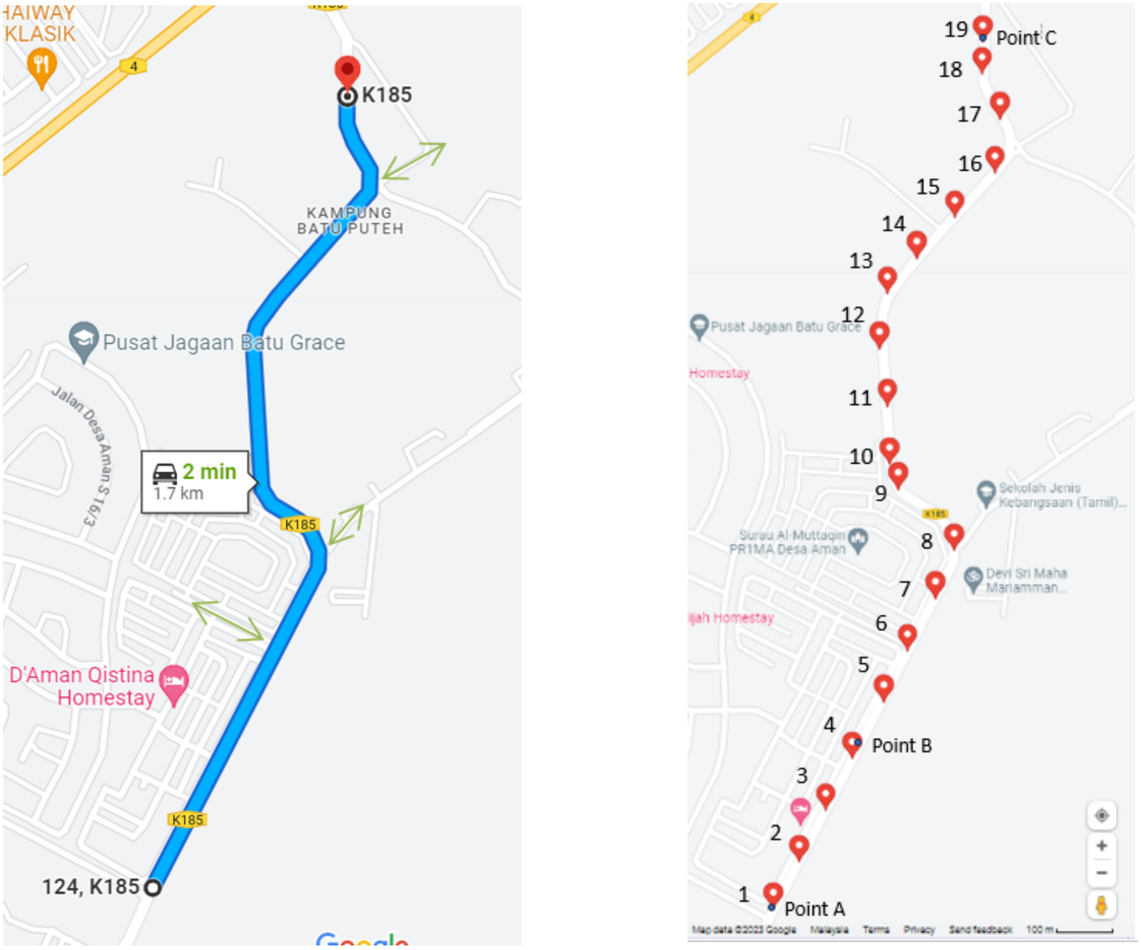
Firstly, we briefly introduce the method used to predict travel time using road geometry.

i. A set of data point along the chosen route is extracted from GPS
ii. Curvature information at each data point is obtained by using three-point fitting technique
iii. Speed profile for each road segment is calculated from the curvature information. Speed profile is constructed based on these assumptions:
    a. the driver will not drive more than the safe or design speed at any particular point of the road
    b. the driver will not drive more than the initial average speed
iv. Initial average speed of the driver is obtained by observation and it is assumed to be the average speed throughout the driving.
v. Travel time is computed for each road segment.

For details and formulation, please refer to Ramli *et al.,* [17].

Next, we have conducted an experiment in a section of Jalan K185, Desa Aman, 09400 Karangan, Kedah. The aim of this experiment is to see the reliability of the method for cars and trucks. The experiment was conducted on 21st February 2023 for 63 minutes from 4:15 PM to 5:18 PM.

Figure 1(a) depicts a 1.7 km rural road segment with multiple turns that is frequently used by locals. We recorded the vehicles that traversed from Point A to Point C as shown in the picture Figure 1(b). The straight part of the road which is from Point 1 until 8 are intentionally chosen as the initial part of the road segment to get a more accurate value of initial speed. Here, the initial average speed of the driver will be selected as this part of the road lets the driver to drive at their own pace. This road segment contains three junctions, marked with two ways arrow. Any vehicles coming from and exiting the route from these junctions will not be counted into the experiment as they did not complete the full route.



(a) (b)

Fig. 1. (a) Road map (b) 19 data points along Jalan K185. Both are taken from Google [18]

We recorded videos in three checkpoints to obtain the time passed at the location. The time taken at Checkpoints A and B is used to compute the initial average time. Technically, the travel time can be predicted based on this information. The time taken at Checkpoint C is then used to verify the accuracy of our predicted travel time.

We recorded videos in three checkpoints to obtain the time passed at the location. Figure 2 shows the captured video which recorded the specific time the car is passing Checkpoint A. Using a mobile application called Timestamp Camera, the video also recorded the coordinate of the camera. However, we compute Checkpoint A based on a specific point where the car passes, not the observer location. For example, in Table 1, we have summarized the time taken by car #2 as it passes through all three checkpoints.

Fig. 2. A screenshot from the recorded video at Checkpoint A

Table 1
Sample data for car #2

Location	Checkpoint A	Checkpoint B	Checkpoint C
Coordinates	5.496577, 100.628141	5.500314, 100.630062	5.510271, 100.631463
Sample Picture	 Car #2 passes Checkpoint A	 The car passes Checkpoint B	 The car passes Checkpoint C
		 The car after passing Checkpoint B	 The car after passing Checkpoint C
Picture's time taken	4:15:56	4:16:19	4:17:36

3. Results

For every three data points, we interpolate a circular arc to estimate the curvature value of the point on the road. Figure 3 shows the circular arc that interpolates three data points at one time. Figure 3 shows several circles representing curvature at each data point. Smaller circle indicates higher curvature value at that point of road. The higher the road curvature, the higher the need for drivers to slow down their vehicle. Highest curvature value is recorded at the 8th point while lowest curvature value is at the third point.

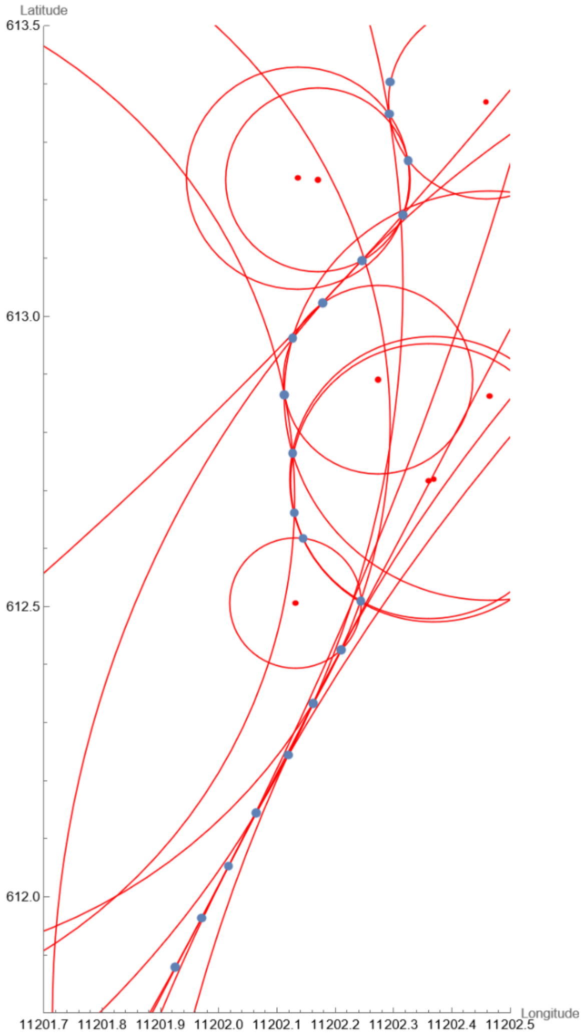


Fig. 3. Compilation of circular arc for each data points (shown as blue dots) along Jalan Desa Aman. Red dots represent the center of circular arc.

The recorded time for truck can be seen in Table 2. The travel time between Point A and Point B is calculated (Column 5) to obtain the initial speed for the vehicle. The initial speed is calculated from Eq. (1). Travel time between A and C is also calculated (Column 7) to compare with the travel time prediction (Column 8). The error between the real data and the predicted time is shown in Column 9. We omit showing the table for car data due to the limitation of space in this paper.

$$Initial\ speed = \frac{distance\ between\ Point\ A\ and\ B}{travel\ time\ between\ Point\ A\ and\ B} \tag{1}$$

Table 3 shows the comparison of error for our method between cars and trucks. There are 64 cars and 19 trucks involved in our experiment. The average error for cars and trucks are 11.41 and 17.58 seconds respectively. We can see that our travel time estimation works better for cars compared to trucks as cars has lower error. The minimum error for cars is one second, whereas for trucks, it is seven seconds. It shows that for certain cases this method is able to predict the travel time almost accurately with only 1 second different. Among all data, the maximum error for a car is 40 seconds, whereas trucks have a maximum error of 51 seconds.

Table 2
Recorded time for truck

#	Time taken at Point A, hh:mm:ss	Time taken at Point B, hh:mm:ss	Time taken at Point C, hh:mm:ss	Travel time between Point A and Point B, hh:mm:ss	Initial speed (speed from Point A to Point B), km/h	Travel time between Point A and Point C, hh:mm:ss	Travel time prediction from Point A to Point C, hh:mm:ss	Error, hh:mm:ss
1	4:16:44	4:17:09	4:18:37	0:00:25	72.00	0:01:53	0:01:36	0:00:17
2	4:19:07	4:19:33	4:21:09	0:00:26	69.23	0:02:02	0:01:38	0:00:24
3	4:21:46	4:22:09	4:23:33	0:00:23	78.26	0:01:47	0:01:32	0:00:15
4	4:24:17	4:24:47	4:26:26	0:00:30	60.00	0:02:09	0:01:47	0:00:22
5	4:25:12	4:25:42	4:27:20	0:00:30	60.00	0:02:08	0:01:47	0:00:21
6	4:27:10	4:27:35	4:28:59	0:00:25	72.00	0:01:49	0:01:36	0:00:13
7	4:37:33	4:37:55	4:39:16	0:00:22	81.82	0:01:43	0:01:31	0:00:12
8	4:41:12	4:41:37	4:43:02	0:00:25	72.00	0:01:50	0:01:36	0:00:14
9	4:41:15	4:41:39	4:43:05	0:00:24	75.00	0:01:50	0:01:34	0:00:16
10	4:44:05	4:44:28	4:45:53	0:00:23	78.26	0:01:48	0:01:32	0:00:16
11	4:48:21	4:48:47	4:50:38	0:00:26	69.23	0:02:17	0:01:38	0:00:39
12	4:49:50	4:50:20	4:51:44	0:00:30	60.00	0:01:54	0:01:47	0:00:07
13	4:54:45	4:55:06	4:56:25	0:00:21	85.71	0:01:40	0:01:29	0:00:11
14	4:58:08	4:58:33	4:59:57	0:00:25	72.00	0:01:49	0:01:37	0:00:12
15	5:05:09	5:05:27	5:06:40	0:00:18	100.00	0:01:31	0:01:24	0:00:07
16	5:05:10	5:05:37	5:07:42	0:00:27	66.67	0:02:32	0:01:41	0:00:51
17	5:05:19	5:05:46	5:07:14	0:00:27	66.67	0:01:55	0:01:41	0:00:14
18	5:15:37	5:16:02	5:17:24	0:00:25	72.00	0:01:47	0:01:37	0:00:10
19	5:15:46	5:16:06	5:17:26	0:00:20	90.00	0:01:40	0:01:27	0:00:13

Table 3
Error analysis

Sample	Car	Truck
Number of vehicles	64	19
Minimum error, s	1.00	7.00
Average error, s	11.41	17.58
Maximum error, s	40.00	51.00

We can also see from the histogram in Figure 4 for cars and Figure 5 for trucks. The proposed method can accurately estimate the travel time where 38 cars (59.38%) have error that is less than 15 seconds. On the other hand, for trucks, 10 units (52.63%) have error less than 15 seconds.

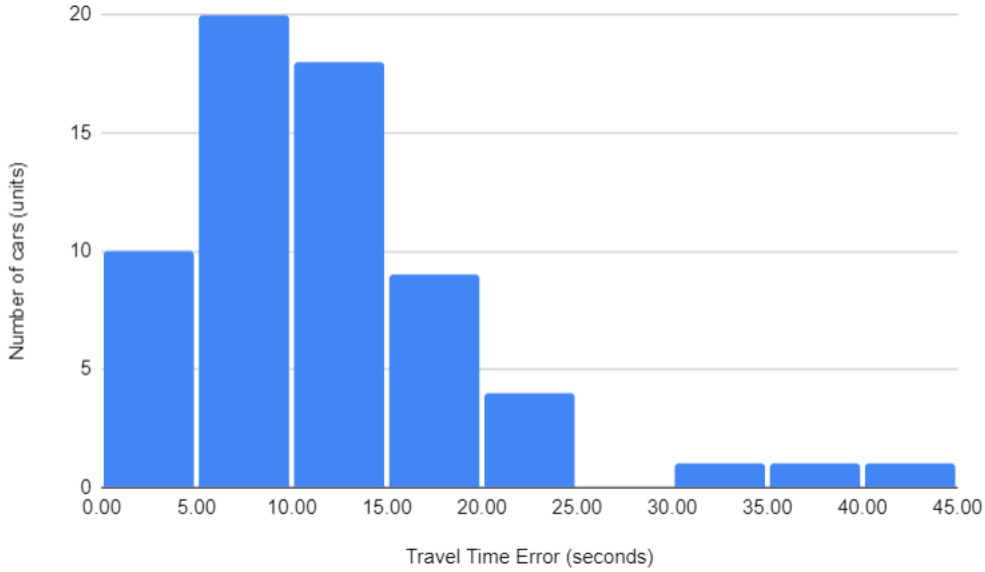


Fig. 4. Travel time error distribution for cars

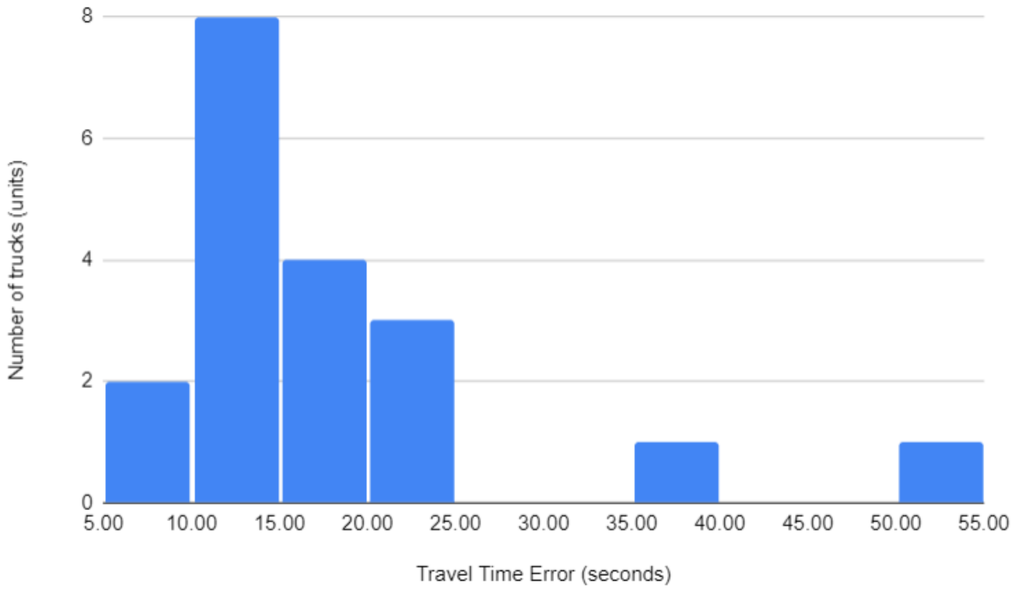


Fig. 5. Travel time error distribution for trucks

4. Discussion

This method is best used for road with less traffic since we only include road geometry factor into our calculation. For congested road, we believe that this method still works with an acceptable error as shown in Table 2.

Firstly, if we observed the error for car data, we would see that there is at least a case where the prediction is off by 40 seconds. As the observed road is not congested neither high in traffic, we can deduce that the car may drive slower than expected speed. Therefore, if the car is not driven at a consistent speed, our prediction will be less accurate.

We have compared the results for cars with trucks and observed that travel time prediction for trucks is less accurate compared to cars. We believe trucks is more influenced by the road geometry causing it to travel at below its average speed. For the truck case, the minimum and average is higher compared to time prediction for car. We can safely assume that the truck would face more difficulty in retaining a consistent speed throughout the road due to its heavy feature.

Looking at 1 km range for a truck drive, SA-LSTM + Savitzky–Golay filter and SA-LSTM + Butterworth low-pass filter gave a Mean Absolute Error (MAE) of 0.1215 minutes per kilometre and 0.2096 minutes per kilometre [19]. Our MAE is 0.1724 minutes per kilometre which that our method produces a more accurate result compared to SA-LSTM + Butterworth low-pass filter but is less accurate compared to SA-LSTM + Savitzky–Golay filter. Our proposed approach can be improved by incorporating a delay factor but is left for future work.

The findings of our study shed light on the effectiveness of utilizing road geometric data for travel time prediction. By comparing the results for car and truck travel, we can draw insights into the varying accuracy and reliability of prediction models based on different vehicle types. Furthermore, we can examine our results in the broader context of previous studies in this field.

Previous research has recognized the significance of road geometric data in improving travel time prediction accuracy [17]. Studies have shown that incorporating spatial and temporal characteristics of road networks, such as road geometry, traffic flow patterns, and intersection configurations, can lead to more precise and reliable predictions [20]. Our study aligns with these findings, as the analysis of geometric data contributed to capturing the complexity and dynamics of the transportation system, enhancing the accuracy of travel time predictions.

5. Conclusions

In this paper, we compare Ramli's method [17] of travel time prediction between car and trucks. Testing the algorithm on a 1.7 km road in Kulim, Kedah, we observe its reliability of prediction on cars and trucks. In low dense traffic area, the result gives a considerably good prediction for cars while expectedly producing a higher error for trucks. Travel time prediction for truck can be adjusted with a certain factor. However, we do not obtain the generalize value for all cases for the current paper.

To increase accuracy in initial driving time, we suggest observing the speed on an extended period of driving. This would be achievable easily if the prediction is programmed on an apps that recalculate initial driving time along the road.

The novelty of this approach is that it uses road geometry for estimating time prediction. Our experiment verifies that it is reliable in the low-dense traffic setting. However, it contains limitation when the road has highly dense traffic. For future research, we wish to combine this geometric approach method with stochastic method and include traffic data for a better estimation.

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