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Development prediction algorithm of vehicle travel time based traffic data

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ABSTRACT

This work is based on encouraging a generous and conceivable estimation for modified an algorithm for vehicle travel times on a highway from the eliminated traffic information using set aside camera image groupings. The strategy for the assessment of vehicle travel times relies upon the distinctive verification of traffic state. The vehicle velocities are gotten from acknowledged vehicle positions in two persistent images by working out the distance covered all through elapsed past time doing mollification between the removed traffic flow data and cultivating a plan to unequivocally predict vehicle travel times. Erbil road data base is used to recognize road locales around road segments which are projected into the commended camera images and later distinguished vehicles are assigned to the looking at route segment so instantaneous and current velocities are calculated. All data were effectively processed and visualized using both MATLAB and Python programming language and its libraries.

Keywords: Prediction Algorithm, Travel Times, Universal Transverse Mercator (UTM), Polygon of Traffic Data

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1. Introduction

The continuous pattern of urbanization and populace development in the urban areas makes it important to have satisfactory methods for road traffic checking [1]. Although many authors have successfully employed a wide variety of traffic prediction and automatic incident detection methodologies, accurate and reliable models for practical use are still not fully functioning [2]. Most of the studies related to travel time prediction were done since the traffic flow is uninterrupted [3]. Intelligent Transportation Systems (ITS) has turned into a functioning exploration region given its capability to advance framework productivity and decision-production [4]. Path location depends on the grouping of directions of vehicles. They are utilized arrangement of Kalman channels that a track needs to pass to be treated as a vehicle and complete mechanization of the framework [5]. As of late, analysts have moved to profound learning-put together strategies and centered with respect to planning new brain network designs to catch noticeable spatial-transient examples shared by all traffic series [6][**7**]. They proposed an Adaptive Graph Convolutional Recurrent Network (AGCRN) to catch fine-grained spatial and fleeting relationships. They normally model fleeting conditions with repetitive brain networks e.g., Long-Short Term Memory and Gated Recurrent Unit or worldly convolution modules [8][9]. As to relationships, they regularly use GCN-based strategies to display unstructured traffic series between conditions. Exact vehicle order and following are progressively significant subjects for clever vehicle frameworks (ITSs) and for arranging that uses exact area insight [10]. Deep Learning (DL) and PC vision are savvy techniques [11][12]; notwithstanding, precise continuous grouping and following accompany issues. Stream with the traffic is appropriate to foresee vehicle travel times yet the data is segmented concerning wide region inclusion and inhumane toward transient blockages [13]. It is essential to perceive the traffic states for each segment before starting the assumption [14]. Concentrates on show that the thickness stream connection isn't ceaseless between free-stream and blocked states which can adjust the vehicle travel times, it's expressed those misjudgments happens sometimes with the double circle sensors and hence prompts dropping the framework accuracy to as low as 53% [15]. Travel times, be that as it may, experience the ill effects of the fleeting and spatial total of skims [16]. While breaking down movement time-subordinate migration choices in the land utilize model, travel hostage families will generally respond all the more delicately to the travel level of administration when individual travel times are utilized [17]. The percentile values used have a statically importance and they are normal as exemptions [18]. The endpoints used in this assessment are 5%ile and 95%ile [19]. One more opportunity is taking the center worth which isn't influenced by couple of exemptions [20]. This is done to obliterate another mistake associated with the driving heading. The results made by this assessment are still in the appraisal stage anyway can be made available to the emergency and security relationship to follow the continuous traffic situation and decide the activities of the best district [21][22]. Further investigation can focus on predicting travel times even more definitively [23]. As recently referenced, a few different endeavors have been made to foster comparative arrangements of ways of behaving and conditions that are significant, likewise as of late delivered a wellful security self-evaluation that incorporated a rundown of conduct capabilities far more than those remembered for the way examination [24-29]. The remainder of the exploration is coordinated as follows: in section (2); The expectation of vehicle travel times had been portrayed. Area (3) building road segments/segments by making polygons is executed, with the plan of the. Trial results and the virtual experience are portrayed in section (4). At long last, ends with analyzations about the outcomes are given in segment (5).

2. The methods

Most urban areas in this present reality extraordinarily depend on the utilization of ground fixed frameworks, e.g., acceptance circles, and traffic cameras for traffic observing on the highways. Vehicle travel times for additional restricted distances are thus known.

2.1. Prediction Algorithm of Vehicle Travel

The outright vehicle travel time for the entire route so far dark due to the segments with no perceived vehicles. Times for those segments should be expected constantly and not sometime soon. One such procedure to anticipate vehicle travel times is by evaluating the unquestionable informational index. The informational index should have contained traffic records showing movements in that particular segment which fluctuate with different days here choice seven consecutive days well similarly with different times during the days. all through the year ought to have been likewise remembered for this data set. The flowchart for the main prediction of travel times of vehicle shown in Figure 1.

The most important stage in accurately predicting vehicle exit times is determining individual vehicle velocities. Accordingly, the data contained in the documents specified in MATLAB (2019b) are consulted for data on the recognized and tracked.

vehicles. These documents contain pixel directions and Universal Transverse Mercator (UTM) for vehicles, are sum all out number of vehicles per picture, the UTM framework comprises of 60 zones, each 6 levels of longitude in width. The UTM secant projection gives around 180 kilometers within accurate scale where the chamber converges the ellipsoid. The scale factor develops from 0.9996 along the focal meridian of an UTM zone to 1.00000 at 180 km toward the east and west. The rightness and culmination of the data assume a significant part in knowing the nature of the removed data. The data contains the UTM directions of similar vehicle two times from the first and second pictures individually. Data is blended in with numbers and strings. The third picture of the burst isn't utilized for following as the first and second picture has a superior crossover to route more vehicles because of a modest hole of 0.6 seconds though the delay is 1.2 seconds between the first and third picture. The singular vehicle velocities are then obtained from the realized vehicle arranged in two successive pictures by computing the distance covered throughout passed time. The slipped by time rises to the time contrast determined between the catching of the first and second pictures of every vehicle. The recipe for ascertaining slipped by time characterizes in Eq. (1). elapsed time = $t_E - t_S$ ------- (1)

Where t_E is the end time, while t_S is the start time. The taking away takes minutes and hours independently. Likewise, the velocity of each individual vehicle followed in each picture are determined and put away. The velocities are put away in an exhibit lattice of a*b where a (lines) is the quantity of vehicles followed and b (segments) is the picture number. The quantity of vehicles (a) followed in various pictures is unique, so a few upsides of velocities are put away as 0 due to the a*b lattice.

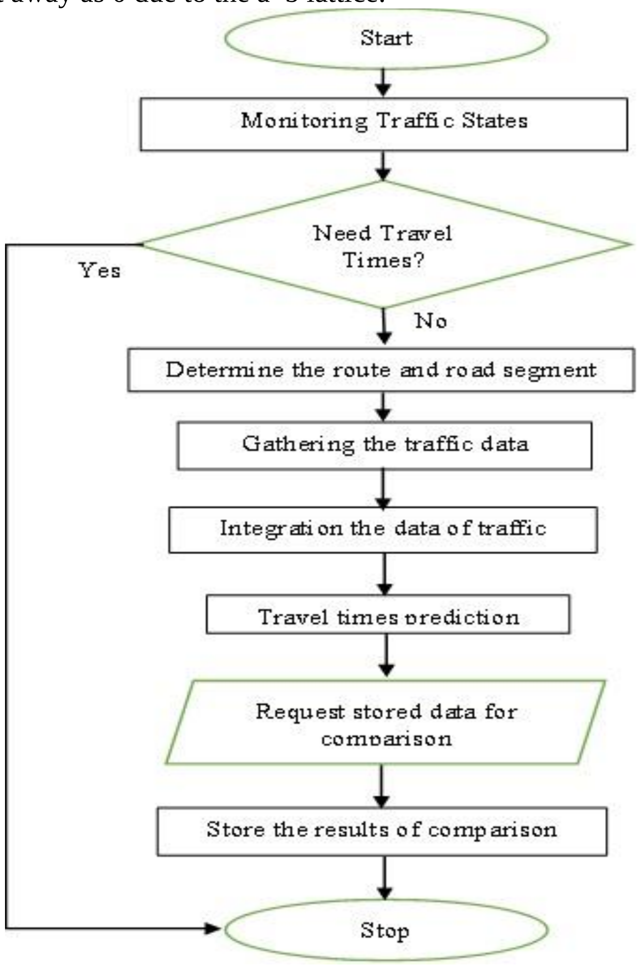

Figure 1. The flowchart for main predict travel times of vehicle

The velocity inferred by the above condition are prompt velocities due to the modest contrast. It tends to be finished by utilizing basic calculation. Vehicle travel times can be anticipated significantly more precisely by considering changing traffic elements by then. These circumstances are utilized to foster a model to foresee vehicle travel times. The procedures of calculate the predict travel time given in algorithm below;

***Step 1*:** Inter the item (route)
***Step 2*:** Determine the traffic flow
***Step 3*:** If unnecessary go to step 8
***Step 4*:** If predict travel time is necessary?
Determine the flow type.
***Step5*:** If Traffic flow is congestion
Then use previous value to predict
***Step6*:** If the flow type not congestion
(Slow moving or Free flow)
then linearly introduce current values
***Step7*:** Else go to step 8
***Step 8*:** calculate the travel time for the entire route

For this model, expectation is thought of as superfluous in the event that vehicle travel times are now anticipated for each segment of the route. This happens once in a while, just when the direction passes along each segment of the route with an earlier condition that vehicles should be recognized in those segments. In any case, the expectation is fundamental in the event that the upsides of vehicle travel times for different segments are missing which is normal in a large portion of the routes. This happens frequently on the grounds that at times the segments are excessively little to contain vehicles in it or on the other hand on the off chance that the free stream is identified on the route, it's excessive that each segment contains vehicles. Figure 2, and Figure 3 illustrated the path with route from Erbil to Dohuk.

Figure 2. The path with route from Erbil to Dohuk

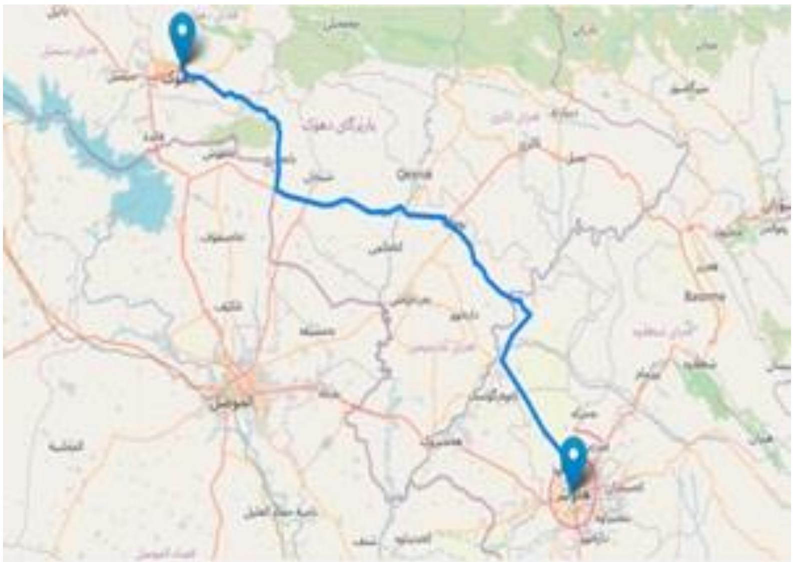

Figure 3. The path between Erbil and Dohuk

2.2. Built road segment polygon of traffic data

In addition, the attractive technique of constructing sections of the road is carried out by making polygons. It is vital for the fabrication of road segments/polygons on the grounds that the boundaries of these polygons are used to make a judgment assuming that the UTM directions of the vehicles followed are inside or outside the drawn segment. The width of the route at each point is known as the "number of lanes" indicated in the documents. The polygons are made by looking at the number of lanes for each address, this way eliminating a wide variety of different vehicles going in the misleading direction or different lanes. Figure 4 shows the bearings/bolts 1 and 2 on the right half of the ascent line being satisfactory since the lateral development of the vehicle can be visualized during the lane change method or during a bend on the road.

However, the different addresses 3 and 4 are not suitable because the car is moving in the other direction of the road. This specific isolation is completed to reject vehicles from the other direction where they can have an alternate state of traffic flow. In any case, these vehicles are naturally remembered for road segments of the other way hence bringing about no deficiency of identified vehicles. On all routes there are 12 routes that are displayed in different shades of blue, red and dark. The road segments are then drawn by the directions and cover the full park road width for each of the

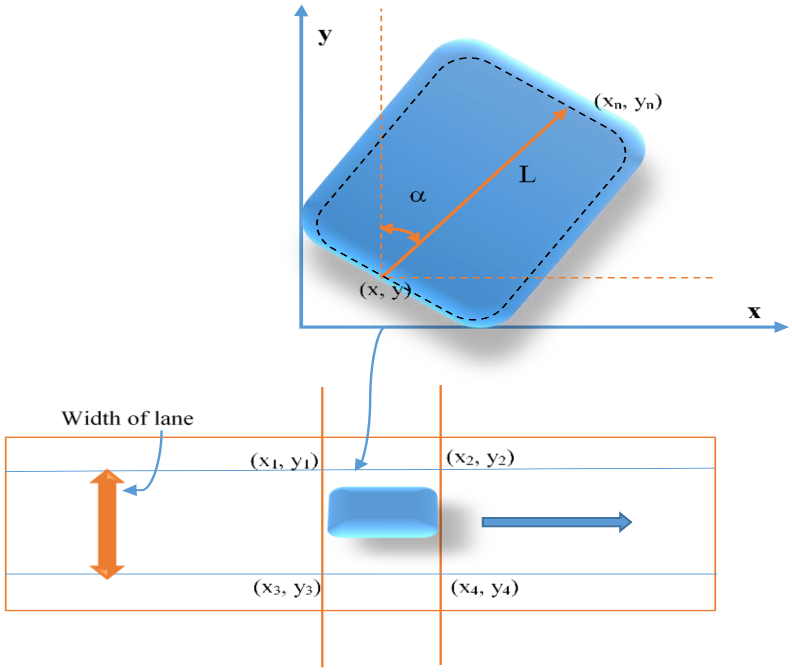

Figure 4. Building a road polygon with driving directions

twelve trails made by calculating the Erbil dataset as shown in Figure 5. Whatever the case, the twelve inferred routes are actually aggregated into two routes Just by adding hubs to two records just to rearrange and better correlate the vehicle's travel times.

Figure 5. Road segments (12 routes)

This path is reformulated to find the four corners of the entire path. The second axis in the main road polygon turns into the main axis in the next guarantee of the section boundaries. The length of the segment varies according to the regulation of the centre line (axes). The In-Polygon capability is used to pick out each of the vehicles (focus points) located within each section of the road along each route. The road polygons are framed by the accompanying motif:

(x, y) = UTM coordinates of the 1st route

(x_n, y_n) = UTM coordinates of the 2nd route

(x_1, y_1) (x_2, y_2) (x_3, y_3) (x_4, y_4) = UTM coordinates of 1st, 2nd, 3rd and 4th corner of the polygon respectively

$\delta = \text{number oflanes} * \frac{\text{lane width}}{2}$ --------(2)

L = Length of the segment

The conditions used to compute the precise places of the four corners of a polygon delineated in Figure 4.

$\tan\alpha = \frac{\text{change in x coordinate of both 1st and 2nd corner}}{\text{change in y coordinate of both 1st and 2nd corner}} = \frac{x - x_n}{y - y_n} = \frac{\Delta x}{\Delta y}$ -------- (3)

$\Delta x_1 = x_1 - x = \delta \cos(\alpha + 90)$ -------- (4)

$\Delta x_2 = x_2 - x = \delta \cos(\alpha - 90)$ -------- (5)

$\Delta x_3 = x_3 - x_n = \delta \cos(\alpha + 90)$ -------- (6)

$\Delta x_4 = x_4 - x_n = \delta \cos(\alpha - 90)$ -------- (7)

$\Delta y_1 = y_1 - y = \delta \sin(\alpha + 90)$ -------- (8)

$\Delta y_2 = y_2 - y = \delta \sin(\alpha - 90)$ -------- (9)

$\Delta y_3 = y_3 - y_n = \delta \sin(\alpha + 90)$ ------- (10)

$\Delta y_4 = y_4 - y_n = \delta \sin(\alpha - 90)$ ------- (11)

Thus, different vehicles are obtained for each section of the road after which the length of each segment is known, and the thickness of the vehicle can be determined. The recognized vehicles in those segments are arranged according to their respective segments. While the preset instant speed is arranged according to its own clips and photos. Three factors are made for velocity. It is expected that a set of specific traffic limits will require further examination. The thickness of the vehicle, its speeds, and its distribution over its sectors are calculated. Now, the speed should be summed to an individual value for each section of the road. The densities of each part are now known. Also, the three basic relationships of traffic flow; Flow rate (Fr) in (veh/hr), Density (D) in (veh/km), and velocity (v) in (km/h), were determined according to the fundamental relationships of traffic flow. Traffic limits are scaled to metric units of km/hr and lane/km. While the basic Eq. (12) for traffic flow is given in the equation below:

$F_r = D * v$ -------- (12)

Average travel velocity as well as, velocity indices (ratios of average velocity to free flow velocity) are estimated and used to analyze and compare the other routes, to determine average travel velocity, take number of vehicles traveling over a segment of highway at an instant in time, expressed as vehicles per time per distance in a lane (veh/hr/km) as shown in Figure 6.

Figure 6. Average velocity

The weight ratio (W_r) of the individual vehicle velocity is as given Eq. (13) while the tangible velocity (v_T) and the immediate velocity (v_I) illustrated in Eqs., (14-15) respectively.

$$W_r = m/M \qquad \text{-------} (13)$$

$$v_T = \sum_{i=1}^{M} V_i W_r \qquad \text{-------} (14)$$

$$v_I = \sum_{i=1}^{N} V_i \frac{n_i}{N} \qquad \text{-------}(15)$$

Where m/M is the weight proportion of the singular vehicle velocity (V_i), n = the number of vehicles with a similar velocity, and N = the all-out number of vehicles, v_T is tangible velocity, v_I is the immediate velocity. Average tangible velocity is characterized as the mean velocity of the relative multitude of vehicles in a known get segment over various timeframes and average immediate velocity is characterized as the mean velocity of the relative multitude of vehicles at a particular moment. Accordingly, quick velocity is just the mean of every single determined velocity. The immediate velocity is first accumulated by the pictures and afterward as indicated by the drawn portions. Vehicle travel times in seconds for each segment were anticipated by partitioning the average tangible or immediate velocity over the length of the separate segment.

3. Results and discussion

Find out which parts of the road are most vehicles generated from images, this was achieved by comparing geometrically tracked vehicles with their driving directions, and detected vehicles from roads generated by the polygon. In addition to the coordinates, the file also contains data on the number of lanes at the node position / location, which is very useful for knowing the width of the highway. Traffic conditions are categorized into three scenarios: free flow, slow flow, and congestion. Conditions used for three lanes (lane 1, lane 2, lane 3) are given in Table 1.

Table 1. Conditions of flow for predict travel times, Velocity(km/h)

No. of Lane Type of Traffic flow	Lane1	Lane2	Lane3
Free	$v \geq 60$	$v \geq 60$	$v \geq 60$
Slow	$20 \leq v < 60$	$20 \leq v < 60$	$20 \leq v < 60$
Congestion	$v < 20$	$v < 20$	$v < 20$

Vehicle travel times are then not measured to immediately get the time expected to pass through each segment. The expected adventure time for each segment of the entire route is determined by summing the vehicle travel seasons for each segment. Through a calculation created to predict vehicle travel times normally on the highway, the results are expected to agree with the purchased data set and scrutinize it for accuracy. The final product was obtained for both data sets. Two link paths were identified from each of the datasets for examination: Highway 8 (forward heading) and Highway 9 (reverse direction) indicated in Figure 7. Two physically aggregated paths from Dohuk, one north and one south along the entire route. Road traffic condition can also be predicted by taking a quick look at these generated graphs that display the vehicle's travel times along the entire route. It gives insight that the vehicle is being followed through the entire length of the track. The diagrams for Interstate 8 and Interstate 9 are shown in Figures 8 and 9 separately. The free flow was normal on the roads near Dohuk while the blockage was normal in the reverse direction of the road near Erbil in light of the commuters heading home as shown in Figure 10. The results indicate that Figure 10 shows the portion of the road facing traffic stops and long delays that can use it to mark the obscured area on the road. In general, these Figs. show a smooth straight line depicting a smooth flow of traffic. Average travel speeds files predict the average free-traffic speed ratios and are used to examine and reflect on the different routes presented in Figure 11.

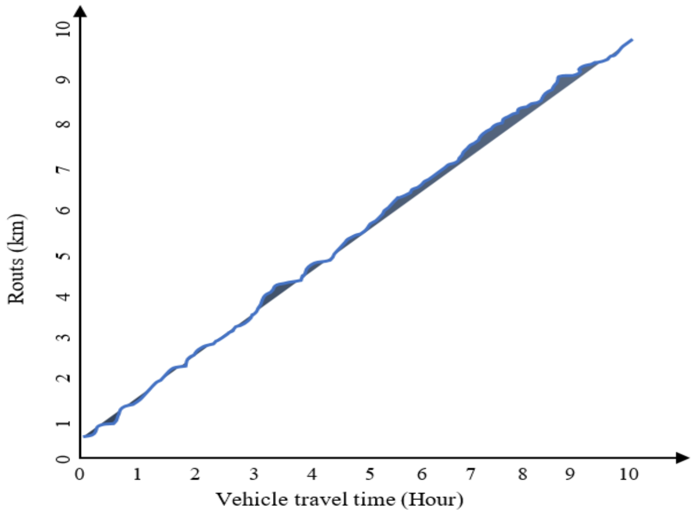

Figure 7. Route 8, forward direction, Dohuk

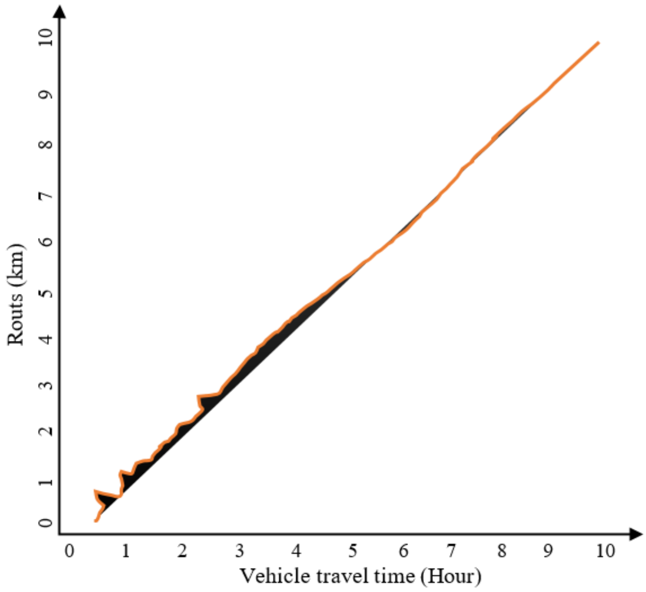

Figure 8. Route 9, backward direction, Dohuk

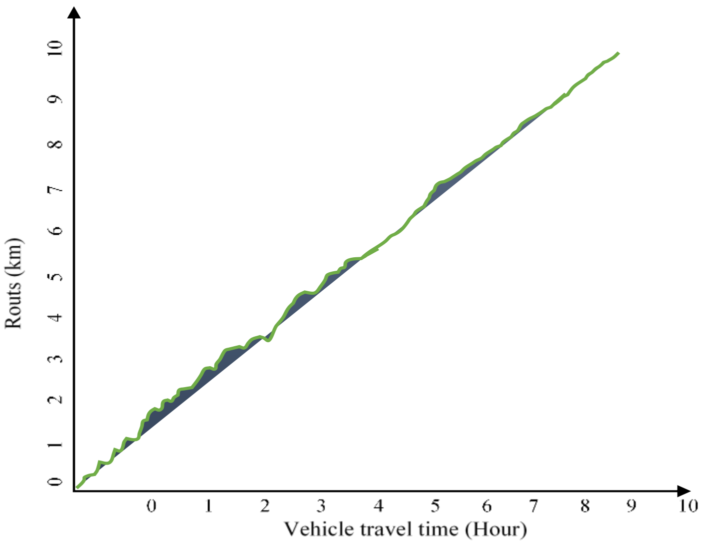

Figure 9. The segment of the route from Erbil to Dohuk

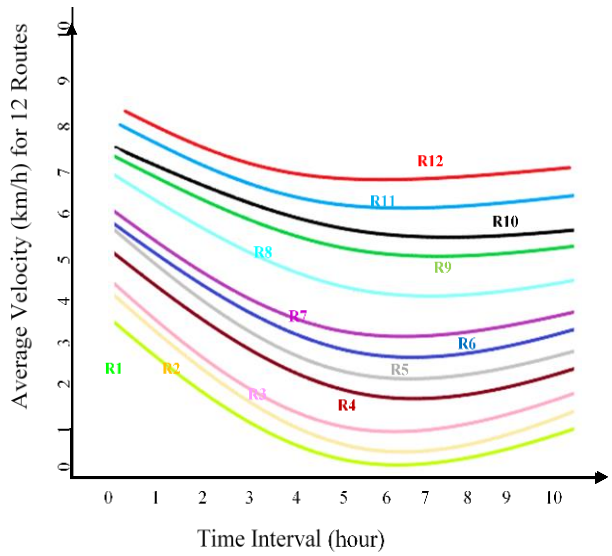

Figure 10. The average velocity

There are sure errors in the primer examination which can impact the outcomes. To come by precise outcomes, the oversight of such inconsistencies is fundamental like how much anomalies. If the vehicle's set speed is less than 10 km/h on a highway where free flow is specified, it is considered an exception. Expected travel times with average immediate velocity and average tangible velocity produce the same curvature in the graphs. The distinction in travel times created by these two speeds for all routes with two types of traffic flows is shown in Tables 2 and 3. Discrimination in expected full travel time is high during occlusion due to the way in which typical average immediate velocities contrast significantly with average tangible velocities when there are a lot of exceptions in the data.

Table 2. Travel times predicted by average immediate velocity and average tangible velocity for free flow

Route No.	Type of Traffic Flow	Rout Length (km)	Total travel time (hour)		
			Tangible	Immediate	Difference
Route 1	Free Flow	1.48	1.91	1.97	0.06
Route 2	Free Flow	1.45	1.86	1.91	0.05
Route 3	Free Flow	1.40	1.82	1.86	0.04
Route 4	Free Flow	1.36	1.78	1.82	0.04
Route 5	Free Flow	1.32	1.72	1.76	0.04
Route 6	Free Flow	1.29	1.67	1.70	0.03
Route 7	Free Flow	1.25	1.62	1.66	0.04
Route 8	Free Flow	1.20	1.58	1.63	0.03
Route 9	Free Flow	1.15	1.55	1.57	0.02
Route 10	Free Flow	1.10	1.50	1.53	0.03
Route 11	Free Flow	1.05	1.45	1.49	0.04
Route 12	Free Flow	1.00	1.36	1.38	0.02

4. Conclusion

We can well find in Table 3 that the travel times generated from the identifiers have higher qualities than the expected travel times from the images. This is because of the way the appreciable velocities recorded by the discoverers are obtained from the first and second segment and not from the third segment. The first track is the slowest and the third is the fastest. This distinguishes between first and second track velocities. Data were collected from forecasts to make a general correlation in determining travel times and a data set was made for examination with the two data sets. Traffic limits such as velocities are currently aggregated in two concrete and immediate ways. Hence average tangible and immediate velocities are obtained for each segment which is subsequently used in forecasting travel times. The prediction quality of the Erbil dataset was determined at 94% to 98% which implies that 94% to 98% of the vehicles recognized are followed appropriately. Anyway, for some lanes along the route, travel times are not expected on the grounds that when images were taken, vehicles were absent in those parts. Travel times for these specific lanes are projected in light of different traffic elements.

Conflict of interest

The authors declare that they have no conflict of interest, and all of the authors agree to publish this paper under academic ethics.

Author contributions
All the authors contributed equally to the manuscript.

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