A Network Selection Algorithm Based on Vehicle Trajectory Prediction and AHP

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Abstract. This paper proposes a network selection algorithm based on Vehicle Trajectory Prediction and AHP (VMAP). The Markov chain is used to predict the running trajectory of the vehicle. The predicted trajectory is used to calculate the dwell time of the vehicle in the network. A network in which the dwell time is greater than a preset threshold is selected as a candidate network. Then, using the Analytic Hierarchy Process (AHP) to determine the weights of each attribute of the candidate network and obtain the comprehensive evaluation quality index of each candidate network to select the optimal network. This algorithm can not only minimize the ping-pong effect generated, but also enable the vehicle to access the optimal network stably.

1. Introduction
There are many different wireless technologies in the Internet of Vehicles, including WLAN, 4/5G network, dedicated short-range communication technology (DSRC)[1] and Vehicular ad-hoc network (VANET)[2]. In the hotspot area where multiple wireless networks are simultaneously covered. The vehicle mobile terminal needs to select a suitable network according to the service demand. The vehicles are in high speed motion in the vehicle network. The mobile terminal needs to select the optimal network access in a short time. Therefore, how the vehicle in a variety of networks make the choice of the optimal network during driving has gradually become a key issue in the Internet of Vehicles.

The existing network selection algorithms mainly include:

- based on the signal reception strength algorithm (RSS)[3], this algorithm mainly relies on the received signal strength of different networks collected by the vehicle terminal as the standard for selecting the network and this algorithm will bring frequent Ping-pong effect.
network Switching algorithm based on cost function[4], this algorithm considers more network parameters, such as bandwidth, overhead, delay, etc., which improves the efficiency of network selection compared with RSS algorithm.

• Multi-attribute decision algorithm (MADM)[5], this algorithm focused on solving the problem of ranking and optimization of finite schemes, MADM algorithm is the most widely used strategy in heterogeneous network selection.

The rest of the paper is organized as follows: Section 1 introduces the specific flow of the algorithm; Section 2 introduces the trajectory prediction using Markov chain[6-8] and the calculation method for the vehicle’s dwell time in the network; Section 3 introduces the method of determining the final optimal network access by using the AHP[9-10]; Section 4 introduces the simulation results and the result analysis.

2. Algorithm design

2.1. Trajectory prediction based on Markov chain

The trajectory prediction based on Markov chain mainly relies on the state transition probability matrix to predict the possibility of the vehicle to the next state position. The position of the vehicle in the car network is not discrete, but we can let each intersection as a state point. As shown in Figure 1, the process of driving the vehicle from the intersection X to the intersection O is called: the vehicle travels in the XO direction. If the vehicle is about to pass the intersection O at the next moment, then the vehicle will have three possible driving possibilities (OX, OY and OZ). The above process can convert the trajectory prediction of the vehicle into a point-to-point problem of selecting different driving directions.

![Vehicle in the intersection](image)

**Figure 1.** vehicle in the intersection

Suppose the vehicle travels via the respective intersection position information \( \{ X_n, n \in N \} \) is a random sequence of discrete state space, \( n = 1, 2, ..., N \). According to the nature of the Markov chain

\[
P(X_{n+1} | X_n, X_{n-1}, X_{n-2}) = P(X_{n+1} | X_n)
\]

(1)

Where the next state probability \( X_{n+1} \) only rely on the current state \( X_n \), regardless of the previous state. At the time \( n \), the one-step transition probability of the vehicle moving to state \( j \) under the state \( i \) is:

\[
p_{ij}(n) = P(X_{n+1} = j | X_n = i)
\]

(2)

Where \( p_{ij}(n) \) is abbreviated as \( p_{ij} \). \( p_{ij} \) can be obtained by large number of moving historical trajectory data statistics of the vehicle. Suppose \( N(i,j) \) is the number of times the vehicle gets to the intersection \( j \) at the intersection \( i \), and \( N(i) \) is the number of times the vehicle passes a certain intersection \( i \).

\[
p_{ij} = \frac{N(i,j)}{N(i)}
\]

(3)

A matrix consisting of all one-step transition probability, called a one-step transition probability matrix at a certain moment which is denoted as \( P \). Suppose there are \( M \) junctions, transition probability matrix \( P \) was a second order \( M \times M \) matrix:
For each vehicle, a state probability transfer matrix is derived from its historical trajectory. Scanning the row number of the row corresponding to the \( i \) row according to the current position \( i \) scan state transition matrix row number, wherein the largest column element is the predicted next intersection \( j \), and then substituting the predicted position state into the state probability transition matrix again, Iteratively solves the future trajectory of the vehicle.

2.2 Comparison dwell time

The vehicle trajectory prediction can predict the trajectory of the vehicle at the next intersection. The network coverage is known by the base station attribute, and the road length of the vehicle driving range is known. Then, based on the vehicle speed information reported by the plurality of vehicles in the vehicle network range, the estimated vehicle speed of the front road section can be comprehensively calculated to calculate the dwell time of the vehicle in the front network.

In order to select the candidate connection network, a threshold of residence time can be set in advance. If the residence time of the vehicle in a network coverage area is higher than the threshold, it means that the vehicle stays in the network coverage area for a long time, which is not easy to generate ping-pong effect. Therefore, the network can be used as a candidate network.

2.3 Using the AHP determine the final access network

For candidate networks, the AHP method can be used to select the optimal network among the candidate networks.

The hierarchical structure of the target is shown in Figure 2. It is assumed that the three networks \( E, F \) and \( G \) are selected as candidate networks. Generally, the attributes that have a large impact on the network are transmission rate \( (A_1) \), transmission delay \( (A_2) \), transmission power \( (A_3) \), and outage probability \( (A_4) \). The steps to determine the optimal access network using different network attributes are as follows.

Assume that the network attribute judgment matrix scale definition is as shown in Table 1, and the scale value \( a_{ij} \) indicates the relative importance degree of the attribute \( A_i \) compared to the attribute \( A_j \). For example, assuming that the transmission delay \( A_2 \) is twice as important as the transmission rate \( A_1 \) in the network access of the Internet of Vehicles, \( a_{12} = 2 \), otherwise \( a_{12} = 1/2 \).
According to the influence degree of the four attributes of the standard layer on the network access of the target layer in Figure 2, a judgment matrix of attribute comparisons is established, \( A = (a_{ij})_{N \times N} \), where \( i, j = 1,2,3,4; N=4 \).

\[
A = \begin{bmatrix}
a_{11} & \cdots & a_{1j} & \cdots & a_{1N} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
a_{i1} & \cdots & a_{ij} & \cdots & a_{iN} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
a_{N1} & \cdots & a_{Nj} & \cdots & a_{NN}
\end{bmatrix}
\]  

The feature vector \( W = (\alpha_1, \alpha_2, \ldots, \alpha_N) \) of the judgment matrix \( A \) for network access is calculated, that is, the weight expression form of each attribute in the network. Followed by a consistency check. If the consistency check is not met, the value of the judgment matrix needs to be adjusted until the consistency check is met.

According to the degree of dependence of the three candidate networks of the decision layer in the decision layer on the first attribute of the standard layer in Figure 2, a judgment matrix of pairwise comparison is constructed \( B_1 = (b_{ij})_{3 \times 3} \), where \( i,j \) Corresponding to \( E,F,G \) network. The scale value \( b_{ij} \) indicates the relative dependence of two networks on an attribute. For example, suppose that network \( E \) is dependent on the transmission rate twice as much as network \( F \), then \( b_{EF} =2 \), otherwise \( b_{EF} =1/2 \). The network judgment matrix scale definition is as shown in Table 2. Then, the feature vector \( \theta_1 \) of the judgment matrix \( B_1 \) for the transmission rate is obtained.

| Scale value \( a_{ij} \) | \( \alpha \) |
|--------------------------|----------|
| equally important        | 1        |
| Slightly important       | 3        |
| important                | 5        |
| Very important           | 7        |
| Extremely important      | 9        |
| Median                   | 2,4,6,8  |

| Scale value \( b_{ij} \) | \( \theta \) |
|--------------------------|----------|
| equally important        | 1        |
| Slightly important       | 3        |
| important                | 5        |
| Very important           | 7        |
| Extremely important      | 9        |
| Median                   | 2,4,6,8  |
Using the method above, the judgment matrices $B_2, B_3, B_4$ are constructed according to the degree of dependence of the three candidate networks on the remaining three attributes. And the eigenvectors $\theta_2, \theta_3, \theta_4$ of each judgment matrix for four attributes are respectively obtained. Finally, four eigenvector matrix are combined into $R=(\theta_1, \theta_2, \theta_3, \theta_4)_{3\times 4}$.

Perform the consistency check again. If each candidate network meet the consistency check, it is transferred to perform weighting calculation; if the consistency check cannot be met, the value of the network judgment matrix needs to be adjusted until all the consistency tests are met.

The weighting calculation first calculates the weighted attribute vectors $\delta_E, \delta_F, \delta_G$, and sets the network attribute vectors to $\varphi_E, \varphi_F, \varphi_G$:

$$\delta_E = \varphi_E \ast W, \delta_F = \varphi_F \ast W, \delta_G = \varphi_G \ast W$$

(6)

Where $\ast$ indicates the Hadamard product. Let the matrix formed by the vectors $\delta_E, \delta_F, \delta_G$ be $K=(\delta_E, \delta_F, \delta_G)_{4\times 3}$. Then the transposing the matrix $R$ and the matrix $K$ is calculated by Hadamard product:

$$S = R \ast K^T$$

(7)

The resulting matrix $S$ in the equation is the final composite result matrix. Finally, all the elements of the row vector of each row of the matrix $S$ are added to obtain $s_E, s_F, s_G$ is the $E, F, G$ network comprehensive index value, compare $s_E, s_F, s_G$ three numerical values, The network corresponding to the maximum value is the optimal network.

3. Simulation and analysis

3.1 Simulation environment

The simulation scenario is shown in Figure 3. It is set up as a $2000 \times 2000m^2$ urban area, which contains 36 intersections, each of which is a two-way driving lane.

In the simulation experiment, the vehicle in the heterogeneous vehicle network mainly includes four attributes: network transmission rate, transmission delay, transmission power and interruption probability. The network attribute parameters are shown in Table 3.
Table 3. Network attribute parameters

| network  | transmission rate(Mb/s) | transmission delay(ms) | transmission power(dBM) | outage probability(%) |
|----------|-------------------------|------------------------|-------------------------|-----------------------|
| VANETs   | 10                      | 200                    | 15                      | 10                    |
| WLAN     | 30                      | 800                    | 20                      | 9                     |
| LTE      | 20                      | 500                    | 50                      | 9                     |
| 5G       | 60                      | 100                    | 60                      | 5                     |

In this paper, the experimental simulation is carried out in different speed scenarios of vehicles. The end-to-end average delay and the number of network handoffs of the algorithm (VMAP) and the received signal strength algorithm (RSS) are compared in different vehicle speeds in the same environment.

The end-to-end average delay is the time elapsed for a packet to be sent from the source node to the destination node. The lower the delay, the faster the network transmission.

The number of network handoffs represents the stability of the vehicle connection network. At the same speed, the fewer the number of network handoffs, the less likely it is to produce ping-pong effect.

3.2 Experimental results analysis

3.2.1 End-to-end average delay analysis. Figure 4 is an end-to-end average delay of the vehicle using the RSS algorithm and the VMAP algorithm at different speeds. As can be seen from the diagram, the vehicle speed increases, the average end-to-end delay of both algorithms shows an upward trend to varying degrees. Among them, the delay of the RSS algorithm is very high and the increase is very large. When the vehicle running speed is 5m/s, the delay reaches 546ms. When the vehicle speed reaches 30m/s, the delay is as high as 987ms. The advantages of the VMAP algorithm in this paper are very obvious. Not only in all the vehicle speeds, the delay is much lower than the RSS algorithm and it is very stable. The end-to-end average delay does not rise more than 200ms, which guarantees the quality of the network connection.

3.2.2 Number of network handoffs. Figure 5 is the number of network handoffs diagram at different speeds of the vehicle using the RSS algorithm and the VMAP algorithm. As can be seen from the diagram, the number of network handoffs of the RSS algorithm is always higher than 70 times with the vehicle speed increasing the number of handoffs also increases very fast. The number of network handoffs is as high as 120 times at 30 m/s. Such frequent network handover is bound to be Produce a ‘ping-pong effect’. The VMAP algorithm in this paper always maintains a low number of network handoffs.
handoffs because the network that is prone to ping-pong effect has been excluded by vehicle trajectory prediction and dwell time estimation. In addition, according to the AHP, the access network is guaranteed to be optimal, and the stability of the network link is further improved, thereby reducing the number of network handoffs.

Figure 5. Number of network handoffs

4. Conclusion

The VMAP algorithm excludes the network whose dwell time is lower than the preset threshold. The advantage of this method is ensuring the stability of the subsequent network connection and improves the network selection efficiency. Then the paper uses AHP to select the network. It is ensured that the selected optimal network is not only better than the other candidate networks in one or several attributes, but is better than the other candidate networks after being weighted and compared in many aspects.

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