A Self-adaptive Feedback Handoff Algorithm Based Decision Tree for Internet of Vehicles

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Abstract. In this paper, a self-adaptive feedback handoff (SAFH) algorithm is proposed to address the problem about dynamic handoffs for the Internet of Vehicles (IoVs), aiming at minimizing handoff delay and reducing the ping-pong effect. We first analyze the main attributes and terminal movement trend, and give the respective handoff probability distribution. Based on handoff probability distributions, the structure of multi-attribute decision tree is determined. To update the terminal state, the incremental learning method by feedback mechanism is implemented by adding decision table information at the nodes of the decision tree so as to dynamically catch the splitting attributes of the decision tree. Simulation results show that the proposed SAFH algorithm's time cost is lower than some existing algorithms. Besides, SAFH algorithm also reduces the ping-pong effect and increases the effectiveness of network connections.

Keywords: Internet of Vehicles · Decision tree · Handoff · Feedback decision Mobile Edge Computing

1 Introduction

With the development of the Internet of Vehicles (IoVs) and wireless access technologies, many vehicles are outfitted with special technologies that tap into the Internet access and provide extra benefits to the drivers. For IoVs, when a mobile vehicle node, which is in a network connection state, moves from one Access Point's (AP's) coverage area to another AP's coverage area, the connection control of the mobile vehicle node is needed to ensure the network connection. From the current serving AP to another AP, this process is named as handoff [1]. The network topology changes faster due to the characteristics of vehicle mobility and high speed, resulting in more inner network handoffs [2]. Realizing rapid handoff in the IoVs can ensure that the users' network connection is stable and the application of IoVs can get better supported[1].

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Mobile Edge Computing (MEC) provides an Internet Technology (IT) service environment and cloud-computing capabilities at the edge of the mobile network, within the Radio Access Network (RAN) and in close proximity to mobile subscribers [3]. The aim is to reduce latency, ensure highly efficient network operation and service delivery, and offer an improved user experience. MEC can be used to extend the connected car cloud into the highly distributed mobile base station (BS) environment, and enable data and applications to be housed close to the vehicles. In this paper, we consider an IoVs system that MEC participates in to achieve low latency.

At present, researchers have obtained some research results for the network handoff technology for IoVs [4–9]. The authors in [4] described a location-based handoff scheme of Internet of vehicles. This scheme can accurately predict the points that the vehicle may access and uses a blacklist scheme to eliminate redundant access point in order to reduce the time of scanning access points. In [5], it proposed an urban vehicle handoff scheme based on E-PMIPv6, which can guarantee the continuity of conversation for urban mobile users. It eliminated packet loss to improve handoff performance in each handoff scenario. For the problem of vehicle handoff in mobile micro-cellular networks, the authors in [6] proposed a “mobile extension cell” handoff algorithm. This algorithm focus on outdoor vehicular environments serving end-users with high mobility and it is proved that it is suitable for minimizing packet loss. The authors in [7] reduce handoff delays by predicting vehicle trajectories. To minimizing the handoff cost while satisfying the latency constraints, [7] take a game approach to find the optimal handoff strategies of each type of vehicles. For the problem that existing handoff mechanisms in vehicle networking do not make full use of road information and large handoff delay, the authors in [8] proposed a novel MEC-based handoff mechanism. This mechanism avoided the redundant information exchange between the vehicles and the BS by related deployment operations. The virtual machine migration management solution proposed in [9] first predicted the throughput of the system, and then selected the optimal MEC server for virtual machine migration and handoff. However, the proposed algorithms in the literatures above only presented the utility at the network side, and the terminals’ status, which included the service priority and the terminal movement trend, were not under consideration. In this paper, we jointly consider the network parameters and terminals’ status to build incremental decision tree by feedback mechanism to realize rapid handoff.

The main contributions of this paper are as follows:

1. We propose a self-adaptive feedback handoff (SAFH) algorithm based decision tree to solve ping-pong effect and delay problem for handoffs in IoVs.
2. This paper jointly consider the network parameters, network load of BS, terminal movement trend and terminals’ service requirements to build multi-attribute decision tree.
3. After the vehicle terminal changed its own service state and performed a handoff operation, the vehicle feedbacked decision table information. Incremental learning of the multi-attribute decision tree is implemented so as to dynamically catch the splitting attributes of the decision tree. Consequently, the handoff decision is made according to the rebuilt decision tree.

The rest of this paper is organized as follows: in Sect. 2, the decision tree-based vehicle dynamic handoff algorithm is briefly introduced. Section 3 shows the feedback decision problems based on incremental self-learning algorithm and handoff procedure. And the simulation analysis are given in Sect. 4. In Sect. 5, we summarize the whole work.

2 A Multi-attribute Handoff Decision Based Decision Tree

The system scenario is first described in Sect. 2.1. And parameters of attributes are introduced in Sect. 2.2 because network attributes parameters often affect handoff in IoVs. Then, the decision tree handoff decision method is introduced in Sect. 2.3.

2.1 System Scenario

The system studied in this paper is shown in Fig. 1, it includes vehicle terminals, MEC servers, BSs and cloud center [10]. The vehicle terminals connect to BSs through wireless links. The MEC servers can process and transfer data. It is the edge server which can provide localized cloud services for vehicles. And the handoff decision in this proposed algorithm is performed by the BSs which are assisted by MEC servers. The cloud center connects to MEC severs through the wide area network (WAN). Handoff occurs when the vehicle is traveling between different BSs.

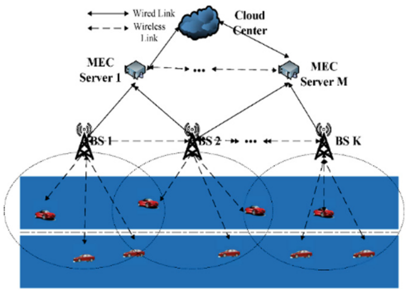

Fig. 1. System scenario

2.2 Multi-attribute Decision

For handoff problem in this paper, we jointly consider the network attribute parameters, terminal movement trend, terminals' service requirements and network load of BS to build decision tree.

A. The Parameters of Network Attribute. The appropriate network attribute parameters are prerequisites for triggering the handoff. Let the target BS network set searched by the vehicle are $S = \{S_k | k = 0, 1, \cdots, K\}$, where K is the total number of target BS, then:

The received signal strength (RSS) reflects the channel quality of the current channel and its expression is:

$$RSS(d) = K_1 - K_2 \lg(d) + \mu(x) \tag{1}$$

Where, K_1 is the transmission power, K_2 is the path loss, K_2 is a constant. d is the distance between the terminal and the BS, $\mu(x)$ is the Gaussian distribution that obeys the parameter $(0, \sigma_1)$, 0 is mean and σ_1 is the variance.

The handoff probability based on the received signal strength network condition attribute parameter is:

$$P_{h1} = P(RSS(d) > \eta) \tag{2}$$

Where, $RSS(d)$ is the target network signal strength, and η is the signal strength threshold required for the terminal to access the network.

B. Terminal Movement Trend. Due to the high-speed movement of the vehicle, the movement tendency, the distance between the terminal and the BS both affect the time for handoffs. The relative movement trend of the vehicle terminal and the BS is shown in Fig. 2. When the vehicle is in position 1, the distance d_1 from the BS 1 is smaller than the distance d_2 from the BS 2. When the vehicle moves to position 2, d_1 is gradually larger than d_2. According to the traditional handoff method, network handoff is required. We use the distance change calculation method to judge the relative motion trend between the vehicle terminal and the BS. It is generally believed that the vehicle's movement trajectory is close to a straight line in a short period of time. The distance between the terminal and the target BS can be calculated from Eq. (1):

$$\Delta D_d = d_2 - d_1 = 10^{\frac{K_1 + \mu(x) - RSS_2}{K_2}} - 10^{\frac{K_1 + \mu(x) - RSS_1}{K_2}} \tag{3}$$

In (3), RSS_1 is the received signal strength between the vehicle mobile terminal and the BS 1, and RSS_2 is the received signal strength between the vehicle mobile terminal and the BS 2. When $\Delta D_d < 0$, it is determined that the terminal is approaching the target BS, which means that the handoff operation needs to be performed; otherwise, it is determined that the terminal is moving away from the target BS.

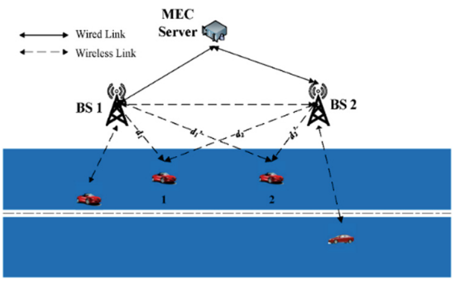

Fig. 2. Relative movement trend between vehicle terminal and BSs

The handoff probability of the terminal motion trend condition attribute is:

$$P_{h2} = P(\Delta D_d < 0) \tag{4}$$

Where, ΔD_d is the distance variation between the terminal and the target BS.

C. Terminal's Services Requirements. Currently, 3GPP defines four basic service types: session services, streaming media services, interactive services, and background services [11]. Among this, the session service has stringent requirements for quality of service (QoS), such as delay and packet loss rate. Therefore, it requires a long network duration. Besides non-conversation services such as streaming media, interactive and background services have a high demand for network transmission rates.

Considering the different services requirements of the vehicle, the network transmission rate is an important index that influences the QoS of the data service and is usually expressed by the link reachable rate as:

$$C_k = Wlb(1 + SNR_k), k = 0, 1, \cdots, K \tag{5}$$

Where, W is the network bandwidth. The handoff probability based on the network transmission rate condition attribute is:

$$P_{h3} = P(\mathrm{C_B} > \mathrm{C_A}) \tag{6}$$

$\mathrm{C_B}$ is the link reachability rate of the target AP's, and $\mathrm{C_A}$ is the link reachability rate of the current AP's.

D. Load Balancing of Base Station. The vehicle's movement between the various BSs will make the number of terminals connecting with each BS have obvious dynamic characteristics. It also causes the load of the BS to exhibit a unbalanced characteristic, making part of the BSs overloaded status, which leads to a decrease in system resource utilization, a higher call blocking rate, thereby affecting the user's QoS experience. The load of the BS is defined as the ratio of the occupied network bandwidth to the total bandwidth provided by the BS network, and let L_k be the network load of the BS S_k. Then L_k can be expressed as:

$$L_k = \frac{\sum_{j \in U_k} B_{jk} x_{jk}}{B_{tot,k}} \tag{7}$$

Where, $B_{tot,k}$ denotes the total network bandwidth of BS S_k, U_k denotes all vehicle sets connected to BS S_k, B_{jk} denotes the service bandwidth requested by the terminal j in the set, and $x_{jk} \in \{0, 1\}$ is the access indication amount of the terminal j. If the terminal accesses the network of the BS S_k, then $x_{jk} = 1$; otherwise, $x_{jk} = 0$. The handoff probability based on the network load balancing condition attribute is:

$$P_{h4} = P(L_A > L_B | L_A > \lambda) \tag{8}$$

Where, L_B is the network load of the target BS, L_A is the network load of the current BS, and λ is the threshold value of the heavy load condition.

2.3 Decision Tree Handoff Decision Method Based on Maximum Probability

When there is a session service in the vehicle service, its requirement for network continuity and call drop rate is high, so the MEC server selects the network duration as a priority. When the terminal service is dominated by non-conversation services, the MEC server considers network bandwidth as the first choice. Others, when the terminal's current BS network load is high, the MEC server considers the load balancing among the BS networks as the first choice. Integrating the load situation of the current BS and the target BS, we give priority to switch the vehicle to the BS network with less load. Based on the above analysis, the tree structure of the decision tree is given in Fig. 3.

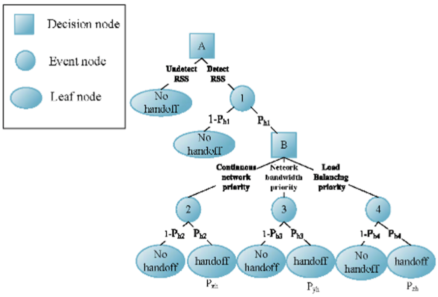

Fig. 3. Structure of multi-attribute decision tree

According to the structure of the decision tree we can get:

$$P_{xhi} = P(h_1)P(h_2|h_1) \tag{9}$$

$$P_{yhi} = P(h_1)P(h_3|h_1) \tag{10}$$

$$P_{zhi} = P(h_1)P(h_4|h_1) \tag{11}$$

The $P(h_1)$, $P(h_2)$, $P(h_3)$ and $P(h_4)$ represent the probability of occurrence of events h_1, h_2, h_3 and h_4 respectively. Therefore, the decision tree-based handoff strategy is a multi-attribute decision based on the maximum probability. That is:

I. When the MEC chooses the network duration priority, If $P_{xh_i} > P_{xh_0}$, we select the ith target BS for network handoff selection; If $P_{xh_i} \leq P_{xh_0}$, the handoff selection is abandoned and the vehicle terminal maintain current network connection.

II. Similarly, when the MEC selects the network bandwidth priority, if $P_{yh_i} > P_{yh_0}$, then we select the ith target BS for network handoff selection, and otherwise the handoff is abandoned.

III. When the MEC selects network load balancing priority, if $P_{zh_i} > P_{zh_0}$, we select the ith target BS for network handoff selection, and otherwise the handoff is abandoned.

Where $P_{xh_i} = \max(P_{xh_1}, \cdots, P_{xh_k})$, $P_{yh_i} = \max(P_{yh_1}, \cdots, P_{yh_k})$, $P_{zh_i} = \max(P_{zh_1}, \cdots, P_{zh_k})$, i represents the ith target BS. And P_{xh_0}, P_{yh_0} and P_{zh_0} are references value of the BS network where the current vehicle terminal is located.

3 Self-adaptive Feedback Handoff Algorithm Based Decision Tree for Internet of Vehicles

During handoff through multi-attribute decision tree, the vehicle movement trend may change. The change of vehicle service status may affect the judgement of the next handoff [12]. Therefore, the self-adaptive incremental learning method based on feedback decision tree is implemented to rebuild the constructed tree.

3.1 Some Definitions About Self-adaptive Incremental Learning

This feedback mechanism implements incremental learning by adding decision table information at the nodes of the decision tree so as to dynamically catch the splitting attributes of the decision tree. Decision table is a special and important knowledge representation system. Decision table is a two-dimensional table, where each row describes an object and each column describes an attribute of the object. Attributes are divided into conditional attributes and decision attributes. According to different conditional attributes, the objects are divided into decision-making categories with different decision attributes. An example of the required decision table is given as follows:

Table 1. Decision table at initial time

	BS network load	Transmission rate	Terminal movement trend	RSS	Decision attribution
1	Medium	High	$\Delta D_d < 0$	High	Y
2	Medium	High	$\Delta D_d < 0$	Low	N
3	Medium	High	$\Delta D_d < 0$	Medium	N
4	Low	High	$\Delta D_d < 0$	High	Y
5	Low	High	$\Delta D_d < 0$	Medium	Y
6	Low	Low	$\Delta D_d < 0$	High	N

Let C indicates condition attributes, $C = \{C_l | l = 1, \cdots, L\}$. In Table 1, C_l are BS network load, Transmission rate, Terminal movement trend and RSS respectively. Let $D = \{Y, N\}$ indicates decision attributes with Y being handoff and N being no handoff. Let E_1 indicates condition class of C_1. In Table 2, $E_4 = \{\text{High}, \text{Medium}, \text{Low}\}$. Let T_l denote the number of cases that satisfy the conditional class being E_l when the decision attribute is Y or N, respectively.

This algorithm uses the greatest overall certainty of the condition attribute to the decision table as selection standard of spilt attributes. The definition of the overall certainty and certainty degree of the decision table is given as follows.

Definition 1. *The overall determinacy of the condition attribute C_l for the decision table is defined as:*

$$\mu_c(C_l) = \sum_{i=1}^{n} \max T_{li}/|U| \tag{12}$$

Where, U is the total data sets, $|U|$ is the count of the total data sets. $i = 1, \cdots, n$, n is the number of each condition class E_l.

Definition 2. *The certainty of the condition class E_l for the decision class is defined as:*

$$\vartheta(E_l) = \max T_{li} \Big/ \sum_{i=1}^{n} T_{li} \tag{13}$$

3.2 The Process of Incremental Learning

The process of the incremental learning is as follows: when a new message is added, the values of μ_c and ϑ are dynamically catched using each decision value stored in each node to determine whether the decision tree needs to be re-adjusted, and the decision tree is re-implemented using the additional information μ_c and ϑ. The great value of μ_c is chosen to be splitting attribute.

At the initial t_1 time, the splitting attribute to start building decision tree is random as the root node is empty. *RSS* is chosen as the root node in this case. Assume that the decision tree generated at the initial t_1 time is shown in Fig. 4, and the root node additional information decision table is shown in Table 2:

Table 2. The root node additional information decision table

	C_1: RSS			C_2: Transmission rate			C_3: Terminal movement trend		C_4: BS network load		
	E_1			E_2			E_3		E_4		
	High	Low	Medium	High	Low	Medium	$\Delta D_d < 0$	$\Delta D_d > 0$	Medium	Low	High
$T_l(\text{D} = \text{Y})$ $l = 1, \cdots, 4$	2	0	1	3	0	0	3	0	1	2	0
$T_l(\text{D} = N)$ $l = 1, \cdots, 4$	0	1	1	2	0	0	2	0	2	0	0
$\vartheta(\text{E}_l)$ $l = 1, \cdots, 4$	1	1	0.5	0.6			0.6		0.67	1	
$\mu_c(\text{C}_l)$ $l = 1, \cdots, 4$	0.8			0.6			0.6		0.8		

After the MEC server performed a handoff operation, if the vehicle feeds back its current state as $(E_1 = High, E_2 = Low, E_3 = \Delta D_d < 0, E_4 = High; D = N)$, the $\mu_c(C_l)$ and $\vartheta(E_l)$ are changed respectively, which are shown in Table 3.

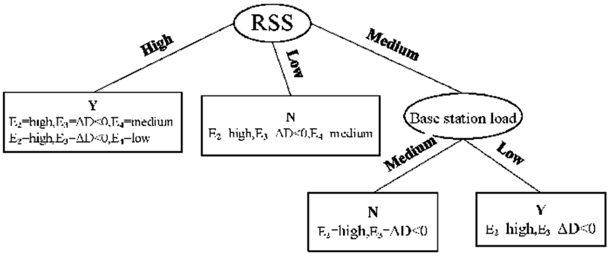

Fig. 4. Decision tree generated at the initial time

Table 3. The root node additional information decision table after feedback

	C_1: RSS			C_2: Transmission rate			C_3: Terminal movement trend		C_4: BS network load		
	E_1			E_2			E_3		E_4		
	High	Low	Medium	High	Low	Medium	$\Delta D_d < 0$	$\Delta D_d > 0$	Medium	Low	High
$T_l(\mathrm{D} = \mathrm{Y})$ $l = 1, \cdots, 4$	2	0	1	3	0	0	3	0	1	2	0
$T_l(\mathrm{D} = N)$ $l = 1, \cdots, 4$	1	1	1	2	1	0	3	0	2	0	1
$\vartheta(\mathrm{E}_l)$ $l = 1, \cdots, 4$	0.67	1	0.5	0.6	1		0.5		0.67	1	1
$\mu_c(\mathrm{C}_l)$ $l = 1, \cdots, 4$	0.67			0.67			0.5		0.83		

Table 4. Medium classification node additional information table

	C_1: RSS			C_2: Transmission rate			C_3: Terminal movement trend	
	E_1			E_2			E_3	
	High	Low	Medium	High	Low	Medium	$\Delta D_d < 0$	$\Delta D_d > 0$
$T_l(\mathrm{D} = \mathrm{Y}) l = 1, \cdots, 4$	1	0	0	1	0	0	1	0
$T_l(\mathrm{D} = N) l = 1, \cdots, 4$	0	1	1	2	1	0	2	0
$\vartheta(\mathrm{E}_l)$ $l = 1, \cdots, 4$	1	1	1	0.67	1		0.67	
$\mu_c(\mathrm{C}_l)$ $l = 1, \cdots, 4$	1			0.67			0.67	

From Table 3, μ_c (BS Network Load) = 0.83 becomes the maximum value instead of $\mu_c(\mathrm{RSS}) = 0.8$ in Table 2. Therefore, the BS network load is used as the splitting attribute of the root node. According to Eq. (14), $\vartheta(E(medium)) = 0.67$, $\vartheta(E(low)) = 1$, $\vartheta(E(high)) = 1$ respectively. Since $\vartheta(E(low)) > \mu_c$ (BS Network Load), $\vartheta(E(high)) > \mu_c$ (BS Network Load), $\vartheta(E(medium)) < \mu_c$ (BS Network Load), the nodes corresponding to the Low classification and the High classification serve as leaf nodes respectively, and the condition classification Medium continues to split. Therefore, the Medium branch in Fig. 4 is removed and the remainder is denoted as a temporary decision tree T. The instances of Low and High values in T is moved to the leaf nodes corresponding to the new Low and High categories, as shown in Fig. 5. Then, the additional information table is changed rely on the temporary decision tree T, which is shown in Table 4.

In Table 4, according to Eq. (12), $\mu_c(RSS) = 1$ becomes the maximum value to be a splitting attribute of the node. Therefore, the Medium branch in Fig. 5(b) is replaced by RSS node in Fig. 5(a), as shown in Fig. 6. That is the decision tree using SAFH algorithm.

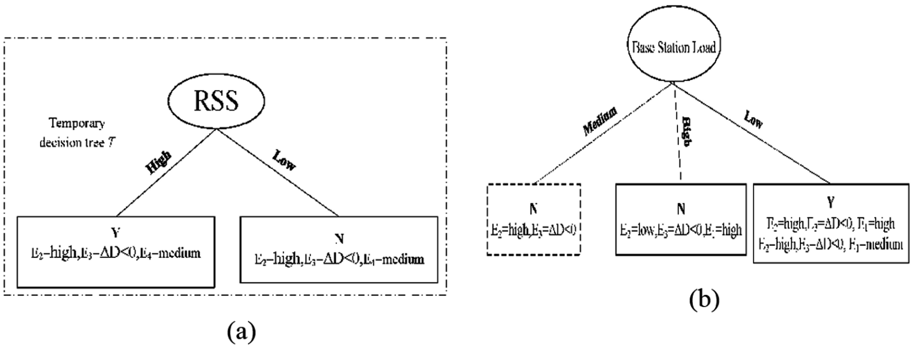

Fig. 5. Decision tree generated at intermediate results

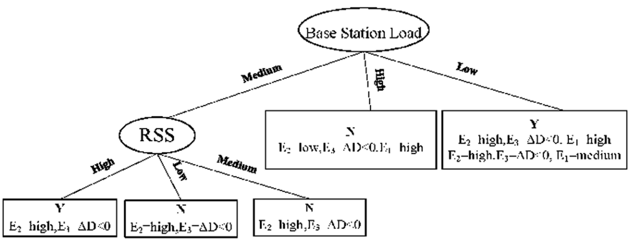

Fig. 6. Decision tree formed after performing a feedback operation

3.3 SAFH Algorithm Based Decision Tree for Internet of Vehicles

In this section, our proposed SAFH algorithm based decision tree is shown in Fig. 7. The two stages of this algorithm are described as follows:

Multi-attribute Handoff Decision Based Decision Tree. The vehicles reports its services requirements to MEC server, MEC server collects network attributes, such as

RSS, transmission rate and BS network load, to calculate handoff probability distribution. Then a multi-attributes decision tree is built to make handoff decision based on maximum handoff according different priorities.

Self-adaptive Feedback Incremental Learning Handoff Method. After the vehicle terminal changed its own service state and performed a handoff operation, the vehicle feedbacked its services requirements and movement trend to MEC server. MEC server update decision table information and incremental learning is used to modify the multi-attribute decision tree. Consequently, the handoff decision is made according to the rebuilt decision tree.

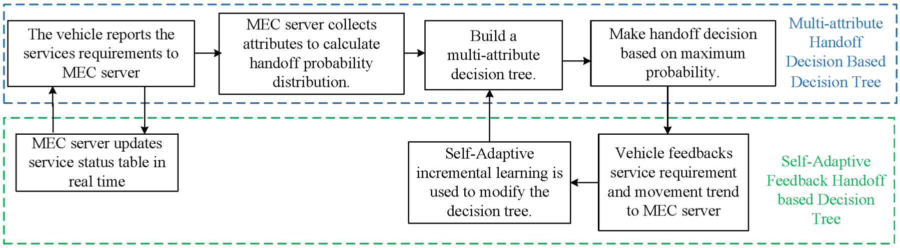

Fig. 7. The flow diagram of SAFH algorithm based decision tree

4 Simulation Results

In this section, we use computer simulations to evaluate the performance of proposed algorithm, and compare the performance of the proposed SAFH algorithm with existing algorithms.

4.1 Simulation Scenario

Based on the system scenario studied in Sect. 2.1, we simulate our proposed SAFH algorithm, comparing with the traditional non-feedback decision tree (NFDT) algorithm [13] and the traditional RSS fuzzy handoff decision algorithm [14]. As shown in Fig. 8, we construct a simulation scenario to evaluate our proposed methods in terms of handoff times and time cost. In the simulation scenario, the signal radius of BS is set to 1000 meters. The signal coverage is circular and the BS is located at the center. In order to facilitate the analysis, the vehicle terminal moves from point A to point E during the simulation. When the vehicle reaches point C, there is session service access. In the simulation experiment, network updating and handover decisions are performed by MEC server every 5 s.

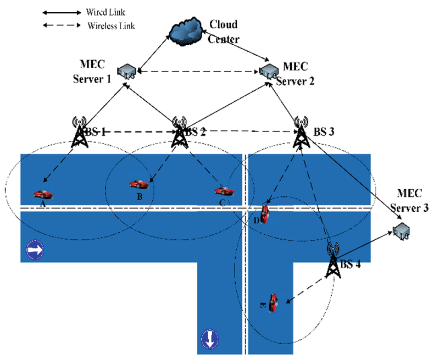

Fig. 8. Simulation Scenario

4.2 Average Handoff Times

When the BS's signal strength changes dramatically in a certain area, the mobile terminal will switch back and forth between the two base stations, which is called the "ping-pong effect" [14]. As shown in Fig. 9, the speed of vehicle is set from 60 km/h to

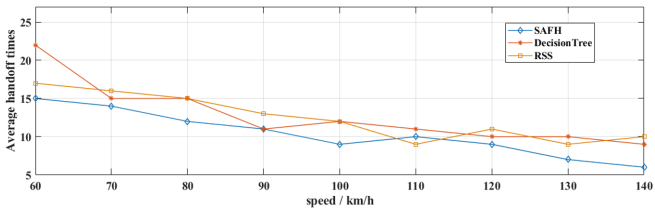

Fig. 9. The average handoff times in terms of vehicle speed

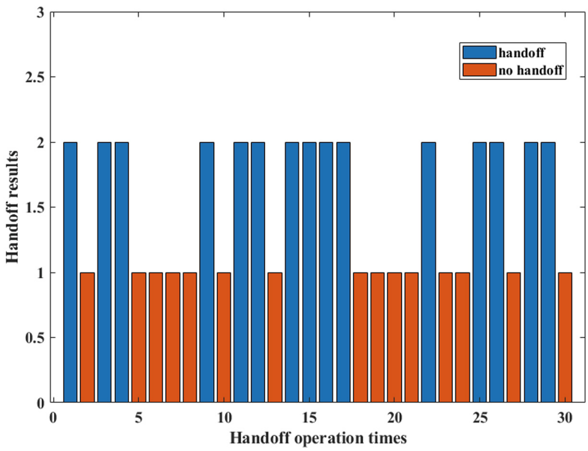

Fig. 10. Handoff case using SAFH algorithm

140 km/h. It shows that the average handoff times decrease as the speed increase. And the average handoff times are lower than NFDT algorithm as well as the traditional RSS fuzzy handoff algorithm. Therefore, the proposed SAFH algorithm can effectively reduce the ping-pong effect, increase the effectiveness of the network connection, and improve the service quality. The Fig. 10 shows a practical handoff case which used the prosed SAFH algorithm, the vehicle terminal experiences 15 handoff operations at a time when its speed is 60 km/h.

4.3 Analysis of Algorithm's Time Cost

We repeated the experiment 10000 times and used the average results to indicate the time cost, because the time cost is a statistical value. From Fig. 11, we can see that the time cost of the proposed SAFH algorithm is generally low. And when the vehicle accessing session service, where travels to the point C, the traditional NFDT algorithm does not have a feedback operation, resulting in a significant increase in time. Besides, the traditional RSS fuzzy handover decision algorithm's time cost is higher than the proposed algorithm. Therefore, the SAFH algorithm proposed in this paper effectively solves the impact on the handoff decisions due to the change of vehicle terminal service status.

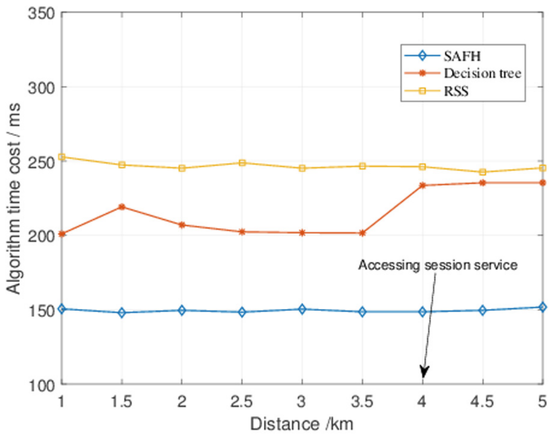

Fig. 11. Preformation time in terms of distance

5 Conclusion

In this paper, we propose a self-adaption feedback handoff (SAFH) algorithm for IoVs based MEC. By vehicle terminal feedback its change of status and movement trends, the MEC server performs pre-trimmed incremental learning on the decision tree to obtain a new type of decision tree. The simulation results show that the SAFH algorithm proposed in this paper is suitable for the handoff decision-making for vehicle terminals with high mobility and frequent business change. The algorithm can effectively reduce the ping-pong effect, increase the effective time of network connection. In addition, our proposed algorithm's time cost is lower comparing with the traditional decision tree handoff algorithm and the RSS-based fuzzy handoff decision algorithm.

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