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Modeling and Analysis for Vertical Handoff Based on the Decision Tree in a Heterogeneous Vehicle Network

BIN MA[1], DONG WANG[1], SHUANGGUO CHENG[2], AND XIANZHONG XIE[2]

[1]Institute of Chongqing Key Laboratory of Computer Network and Communication Technology of China, Chongqing University of Post and Telecommunications, Chongqing 400065, China

[2]Institute of Personal Communications and Chongqing Key Laboratory of Mobile Communications Technology, Chongqing University of Post and Telecommunications, Chongqing 400065, China

Corresponding author: Dong Wang (wangdcqupt@163.com)

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ABSTRACT In this paper, we present an analytical framework to evaluate the accuracy of a vertical handoff algorithm based on a decision tree in a heterogeneous vehicle network. To quantify the effects of errors in the decisions made by this analytical framework, we consider two key design features: 1) the probability of a false alarm and 2) the probability of missing an alarm. Then, we propose using the Kalman filtering algorithm to obtain more accurate parameters. The probability threshold interval model is designed to characterize the errors in vertical handoff decisions made under imprecise information conditions. The accuracy of vertical handoff decisions based on a decision tree under Gaussian and linear models is analyzed. These analytical results are applied to evaluate the performance of the vertical handoff model based on the decision tree. Finally, we propose a robust vertical handoff algorithm based on the decision tree to improve the decision accuracy. A theoretical analysis shows that the proposed algorithm improves handoff decision accuracy. In addition, we conducted comprehensive simulations to validate the theoretical results. The simulation results demonstrate that our algorithm substantially improves the handoff performance in a heterogeneous vehicle network.

INDEX TERMS Decision tree, Kalman filter, vertical handoff, heterogeneous vehicle network.

I. INTRODUCTION

With the development of wireless communication technology, the coexistence of various overlapping networks has become the trend of the future. These overlapping networks provide a variety of communication services for a Mobile Terminal (MT). Consequently, the MTs can select the best network for access, called the ''always best connected'' [1], [2] network. Even though an improved network can provide good support for high-speed users, frequent network handoffs will be triggered in heterogeneous wireless networks for high-speed users. Network handoffs can be divided into two types: 1) a handoff that occur between the same types of networks is called a Horizontal Handoff and 2) a handoff that occur between different types of networks is called a Vertical Handoff. Vertical handoff helps an MT select the best network in an area with networks and ensures that the MT will maintain its desired Quality of Service (QoS). However, the complex topology of heterogeneous networks makes a vertical handoff more difficult to implement. Inaccurate network handoffs cause the MT to switch between multiple networks frequently, a condition called the ''ping-pong effect.'' Consequently, designing an efficient and accurate network handoff algorithm that can ensure MT's maintain an acceptable QoS is of wide concerned to both academia and industry.

Among the current Vertical Handoff (VHO) algorithms, most studies model vertical handoffs as a decision-making process based on collected current network attributes. Then, they conduct a multi-attribute decision-making process. The primary studies are listed below:

1) Handoff algorithms based on utility functions [1], [3]–[9]. Several network attributes are considered in the utility functions, such as, Received Signal Strength (RSS), transmission rate, Bit Error Rate (BER), and Blocking Rate (BR).

2) Handoff algorithms based on fuzzy logic or fuzzy inference [3], [10]–[12] techniques. These works focus on designing fuzzy inference rules and membership functions.

3) Handoff algorithms based on artificial neural networks [13]–[15]. These algorithms can adapt to a changing network environment through learning and cognitive measures. They then transform the complex network handoff problem into an input and output problem in the constructed artificial neural network. The learning time required by these algorithms determines their practicality [24].

4) Predictive handoff algorithms based on a Markov process [16]–[18]. In this approach, a predicted network configuration is used during the decision-making process to improve the algorithm's performance.

5) Handoff algorithms based on thresholds [19]–[23]. Traditional algorithms based on thresholds consider RSS as the main attribute and perform a handoff when RSS meets a certain threshold.

However, the algorithms listed above do not consider inaccurate network attributes resulting from noise interference, which in practical situations can lead to false decisions and a decline in QoS. The high-speed MTs experience rapid changes in network topology, and handoffs will be triggered frequently. Therefore, ensuring the accuracy of the handoff algorithm is highly important in heterogeneous vehicle networks. Algorithms based on thresholds are simple and efficient, therefore, they can be better used in practical network handoff scenarios for high-speed users.

Gani *et al.* [19] analyzed how to achieve seamless connectivity in mobile cloud computing and how to accommodate the mobility and ensure the QoS of an MT simultaneously. According to the hysteresis in the decision process, the author set a residence timer to support both horizontal and vertical handoffs in [20]. The network attributes are insufficient for accurate decision making in traditional threshold-based algorithms; these inaccurate network attributes negatively influence the decision results. In [23], a threshold decision algorithm based on decision tree was proposed to improve handoff performance by constructing different decision branches. However, the problem of errors during decision making still exists in network handoffs under circumstances that involve interference from noise.

In this paper, we first focus on two aspects: obtaining more accurate network attribute values and enhancing the decision accuracy. Then, we propose a robust VHO algorithm based on the decision tree that is intended to solve the high-speed user network handoff problem. We make a detailed analysis of the errors made during key decision points in the traditional VHO algorithm based on the decision tree. Then, considering these main causes of decision errors we employ two enhanced methods that can ameliorate the problems of inaccurate network parameters and the lack of fault tolerance and an error correction mechanism. The two enhanced methods use the Kalman filtering algorithm and the dual-detection (DD) method based on a probability threshold interval (PTI). Our main contributions are as follows:

1) We employ the Kalman filtering algorithm to promote the decision accuracy of the decision tree model, and further quantify the increased decision accuracy after filtering.

2) We design the dual-detection method based on PTI to reduce decision errors caused by noise. Due to the randomness of Gaussian noise, this method enhances the algorithm's fault tolerance and error correcting abilities.

3) We analyze and compare the handoff performance of the proposed algorithm with that of the traditional handoff algorithm based on the decision tree. Then, we quantify the decision error probability of key decision points and the overall decision error probability of the proposed algorithm.

II. ANALYSIS OF THE CURRENT VERTICAL HANDOFF ALGORITHM BASED ON THE DECISION TREE

In this section, we first introduce the current VHO algorithm based on the decision tree [23] and then analyze the probability of decision errors at key decision points in the decision tree. There are two main types of decision error probabilities: False Alarm Probability (FAP) and Missed Alarm Probability (MAP). FAP refers to the probability in which the actual values do not meet the threshold but the decision process assumes that the values do satisfy the threshold. MAP refers to the probability in which the actual values do meet the threshold but the decision assumes that the values do not satisfy the threshold.

A. ALGORITHM DECISION PROCESS

The current handoff algorithm based on the decision tree mainly considers network attributes such as RSS, BER, and BR. First, the networks are screened and classified by the decision tree model. After synthetically considering the decision result at each decision point, the algorithm makes a handoff decision. In Fig. 1, the core part of the decision tree model consists of three major decision points: RSS, BER, and BR.

In this model, the algorithm first evaluates whether the RSS meets an RSS threshold or not. When the RSS meets the threshold, the algorithm calculates the BER and compares it to the BER threshold. When the BER is lower than the BER threshold, the algorithm calculates the network blocking rate. Only networks with low BR values can enter the candidate network set (CNS). From the decision path, we can see that a decision error would lead to two cases: networks with poor QoS enter the CNS or networks with good QoS would not be able to enter the CNS. These two types of decision errors will affect the rationality of the final handoff decision.

B. ANALYSIS OF DECISION ERROR PROBABILITY

First, we quantitatively analyze the probability of making a decision error during the decision-making process.

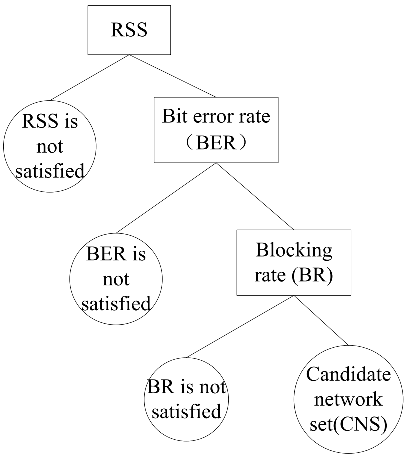

FIGURE 1. The core decision tree.

The decision events for RSS, BER and BR are defined corresponding to the events l_1, l_2 and l_3. Under a situation without noise, $PN_i = 1$ means the decision event l_i satisfies the threshold and $PN_i = 0$ means the decision event l_i does not satisfy the threshold, where $i = 1, 2, 3$. However, in the actual situation, the network attributes are acquired under noise interference conditions. Therefore, the decisions resulting from events l_1, l_2 and l_3 are different from those in the no-noise situation. Here, the decision event l_i satisfies the threshold corresponding to $PD_i = 1$, or, $PD_i = 0$, where $i = 1, 2, 3$. Therefore, the overall decision error probability in the decision tree model is:

$$\begin{aligned} P(\text{FAP}) &= P(PD_1 = 1 \wedge PD_2 = 1 \wedge PD_3 = 1| \\ &\quad PN_1 = 0 \vee PN_2 = 0 \vee PN_3 = 0) \quad (1) \\ P(\text{MAP}) &= P(PD_1 = 0 \vee PD_2 = 0 \vee PD_3 = 0| \\ &\quad PN_1 = 1 \wedge PN_2 = 1 \wedge PN_3 = 1). \quad (2) \end{aligned}$$

Next, we analyze the decision error probability of each decision point showed in Fig. 1 in detail.

1) The decision error probability at the RSS decision point Received Signal Strength is expressed as:

$$RSS(L) = \rho - \eta \lg(L) + n, \quad (3)$$

where L is the distance between the MT and the access point, ρ is the transmission power of the access point, η represents the path loss factor, and n is subject to the Gaussian distribution with parameters of $(0, \sigma_1^2)$. Thus, the correct decision tree branch is selected when RSS meets the minimum RSS threshold,

$$RSS(L) > \varepsilon_1. \quad (4)$$

Thus, the decision error probabilities at RSS decision point are

$$P_{RSS}(\text{FAP}) = P(PD_1 = 1|PN_1 = 0) \quad (5)$$
$$P_{RSS}(\text{MAP}) = P(PD_1 = 0|PN_1 = 1). \quad (6)$$

Based on Eqs. (3)–(6), we transform the decision error probability at the RSS decision point into a standard Gaussian distribution form:

$$P_{RSS}(\text{FAP}) = 1-\Phi(\frac{\varepsilon_1-\rho+\eta\lg(L)}{\sigma_1}), \quad L \geq 10^{\frac{\rho-\varepsilon_1}{\eta}} \quad (7)$$
$$P_{RSS}(\text{MAP}) = \Phi(\frac{\varepsilon_1-\rho+\eta\lg(L)}{\sigma_1}), \quad L < 10^{\frac{\rho-\varepsilon_1}{\eta}}, \quad (8)$$

where $\Phi(x)$ is subject to a standard Gaussian distribution with parameters of (0, 1).

2) The decision error probability at the BER decision point BER is a function of the SNR and can be calculated as follows:

$$SNR(L) = \frac{RSS(L)}{D(L)} \quad (9)$$
$$BER(L) = F(\sqrt{SNR(L)}) \quad (10)$$
$$F(x) = (1/\sqrt{2\pi})\int_x^{\infty} e^{(\frac{-y^2}{2})}dy, \quad (11)$$

where $D(L)$ is the strength of the interfering signal, $D(L) = -130\text{dBm} + u(x)\text{dBm}$, $u(x)$is the Gaussian distribution function with parameters of $(0, \sigma_2^2)$, and σ_2^2 is 10 dBm [23]. We set the BER threshold to ε_2 in decision point; therefore, the condition for a network that satisfies the BER threshold is

$$BER(L) < \varepsilon_2. \quad (12)$$

Obviously, $0 < \varepsilon_2 < 1$. We set $F(\text{t}_0) = \varepsilon_2$; then, we can obtain $\text{t}_0 > 1$ by symbolic calculations. Therefore, the decision error probabilities at BER decision point are given by

$$P_{BER}(\text{FAP}) = P(PD_2 = 1|PN_2 = 0) \quad (13)$$
$$P_{BER}(\text{MAP}) = P(PD_2 = 0|PN_2 = 1). \quad (14)$$

We define, $\theta_1 = \frac{(-2\text{k}-\text{t}_0^2)\text{m}+\rho-\eta\lg(L)}{\text{t}_0^2-\text{k}}$, $\theta_2 = \eta\lg(L) - \rho$, and $\theta_3 = \min(\theta_1, -\text{m})$ when $\text{k} = \sigma_1/\sigma_2$. Further, because the decision error probability is transformed into a standard Gaussian distribution function, we can obtain the following:

$$P_{BER}(\text{FAP}) = \begin{cases} \Phi(\theta_1/\sigma_2) - \Phi(\theta_2/\sigma_2), & \theta_2 < \theta_1 \\ \Phi(\theta_3/\sigma_2), & \theta_2 > \theta_1 \end{cases} \quad (15)$$
$$P_{BER}(\text{MAP}) = 1 - \Phi((\theta_1 - \frac{2\text{km}}{\text{t}_0^2 - \text{k}})/\sigma_2). \quad (16)$$

3) The decision error probability at the BR decision point Network blocking rate is the probability that the network channel is occupied and, consequently, the new service call is blocked. The loss probability is the call loss rate, which can be used to describe the congestion level for terminal calls [25]. According to the Erlang call loss formula, the probability that the terminal's call will be blocked can be described as follows

$$P_q = \frac{A^q/q!}{\sum_{i=0}^{q} A^i/i!}, \quad (17)$$

where $A = \overline{h}s$. $\overline{h}$ is the average number of terminal service calls in normalized time units, s is the duration of the terminal services time in normalized time units, and q is the total number of network channels. The factors that affect the call blocking rate of the terminal are the network system structure, the service call characteristics and strength, and the terminal's service time. If the call number h of terminal business in unit time is subject to a Poisson distribution $p(h) = (\lambda^h/h!)e^{-\lambda}$ and the service time of terminal business is subject to a Gaussian distribution with parameters of (μ_t, σ_t^2), then the average call number should satisfy $\overline{h} = \lambda$. Only networks whose BR is lower than a certain threshold are allowed to enter the CNS:

$$P_q < \varepsilon_3. \tag{18}$$

According to Eqs. (17) and (18), we can obtain

$$(1-\lambda s)(\mathrm{A}_q^1\lambda^{-q}s^{-q} - \mathrm{A}_q^{q-1}\lambda^{-1}s^{-1} + \sum_{i=1}^{q-2}(\mathrm{A}_q^{i+1} - \mathrm{A}_q^{i})\lambda^{q-i}s^{q-i})\lambda^{-1}s^{-1} > \varepsilon_3^{-1}, \tag{19}$$

where $\mathrm{A}_q^i, i = 1, 2, \ldots q$ is the ith permutation value of q. When the total number of channels q and parameters λ are determined, they are regarded as a constant. Let $\mathrm{b} = \mathrm{q}^*\lambda^{-\mathrm{q}}$, $\mathrm{c} = \mathrm{A}_\mathrm{q}^{\mathrm{q}-1}\lambda^{-1}$, and $\{\mathrm{d}_i = (\mathrm{A}_\mathrm{q}^{i+1} - \mathrm{A}_\mathrm{q}^{i})\lambda^{\mathrm{q}-i}, i = 1, 2, \ldots, \mathrm{q}-2\}$. Then, Eq. (19) can be expressed with one variable s:

$$\lambda^{-1}s^{-1}(1-\lambda s)(\mathrm{b}s^{-\mathrm{q}} - \mathrm{c}s^{-1} + \sum_{i=1}^{\mathrm{q}-2}\mathrm{d}_i s^{\mathrm{q}-i}) > \varepsilon_3^{-1}. \tag{20}$$

From Eq. (20), we can see that deviations in the value of the variable s can change the value of the left side of the expression and further affect the result of decision. Any reduction of the forecast deviation of s can get more accurate parameters. Because the variable s in Eq. (20) is the multiple additive structure of high order terms, it cannot be completely separated. Consequently, there is no exact expression for the false decision probability at the BR decision point.

III. THE ROBUST VERTICAL HANDOFF ALGORITHM BASED ON THE DECISION TREE

In this section, we propose a robust VHO algorithm based on the decision tree depicted in Fig. 2. The two stages of this algorithm are described below:

1) Network screening and CNS-generating phase: The networks detected by the MT will enter the decision tree to be screened. The resulting decision determines which networks can enter the CNS. During the decision process, we employ the Kalman filter algorithm to obtain more accurate network attributes and design the DD method based on PTI to enhance the algorithm's fault tolerance and error correction capabilities.

2) Handoff execution phase: If we can obtain the CNS during the first phase, the algorithm will generate multiple decision value attributes for each network in the CNS. The network with the maximum multiple-attribute decision value

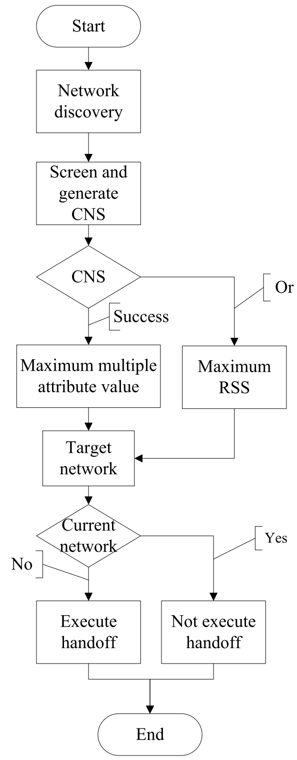

FIGURE 2. **The robust VHO algorithm.**

is selected as the target network. Motivated by the mechanism of an operating system translation lookaside buffer (TLB), we create a Quick Search Table (QST) to optimize the search process for network parameters. If we fail to obtain the CNS during the first phase, then the algorithm selects the network with the maximum RSS as the target network.

A. USING THE KALMAN FILTER TO OBTAIN MORE ACCURATE NETWORK ATTRIBUTES

We use the Kalman filter algorithm to improve the accuracy of the network attributes by calculating the current network attributes based on the predicted values and the current measured values in the system, combining these with their respective noise deviations [26]. We assume that the RSS at the last time period is $RSS(m-1)$ and that the network interference intensity is $D(k-1)$. Meanwhile, their Gaussian noise deviations are denoted as $noise(m-1)$ and $noiseD(m-1)$, respectively. The current measured RSS is $RSS(m)$, and the Gaussian noise deviation of the measured value is $noise(m)$. The measured interference intensity is $D(m)$, and its noise deviation is $noiseD(m)$. $RSS\_cal(m)$ indicates the predictive value of RSS, and $D\_cal(m)$ indicates the predictive value of noise. The filtering algorithm is designed as shown in Algorithm 1.

B. SET THE PTI TO ENHANCE THE ALGORITHM'S FAULT TOLERANCE AND ERROR CORRECTION CAPABILITIES

The traditional handoff algorithm based on the decision tree cannot cope with boundary values very well under exact

Algorithm 1 Filter Optimization Network Attributes Acquisition Method

01: To start, record and maintain the attribute values of the network and the noise deviation during the last period:

$$RSS(m-1),\ D(m-1),\ noise(m-1),\ and\ noiseD(m-1).$$

02: Detect and record the attribute values of the network and the noise deviation at the current period:

$$RSS(m),\ D(m),\ noise(m),\ and\ noiseD(k).$$

03: Calculate the Kalman gain

$$Kg_{RSS}(m) = noise(m-1)^2/(noise(m-1)^2 + noise(m)^2)$$
$$Kg_D(m) = noiseD(m-1)^2/(noiseD(m-1)^2 + noiseD(m)^2)$$

04: Predict the attribute value at the current moment using the values from the last moment.

$$RSS\_cal(m) = RSS(m-1) + \eta \lg(L(m-1)) - \eta \lg(L(m)),$$
$$D\_cal(m) = D(m-1)$$

where $L(m-1)$ is the distance between the MT and the access point at the last moment, while $L(m)$ is the distance at the current moment.

05: Calculate the attribute value of the network at the current moment:

$$RSS(m) = RSS\_cal(m) + Kg_{RSS}(m) * (RSS(m) - RSS\_cal(m))$$
$$D(m) = D\_cal(m) + Kg_D(m)^*(D(m) - D\_cal(m))$$

06: Calculate the noise deviation of the network attributes and update the noise deviation and network attributes:

$$\sqrt{(1-Kg_{RSS}(m))^* noise(m-1)^2} \rightarrow noise(m-1),$$
$$\sqrt{(1-Kg_D(m))^* noiseD(m-1)^2} \rightarrow noiseD(m-1),$$
$$D(m) \rightarrow D(m-1)$$

07: End.

08: Iterate steps: 01∼07 based on the MTs' movement.

thresholds, which always leads to an incorrect decision when the real network attribute is close to the threshold under noise conditions. Considering Gaussian noise characteristics in which most noise values are near the expected values, we set a PTI and use a twice-repeated detection to make the decisions for those attribute values that fall into the PTI (boundary value). Due to the randomness of noise, this repeated detection can reduce the probability of accidental error. We considered the three important sections of Gauss distribution in statistics. Assuming that $X \sim (\mu, \sigma^2)$, μ is the average value of X, and σ is the standard deviation; therefore, the areas of the intervals $[\mu-\sigma, \mu+\sigma]$, $[\mu-1.96\sigma, \mu+1.96\sigma]$, and $[\mu-2.58\sigma, \mu+2.58\sigma]$ are 68.27%, 95.00%, and

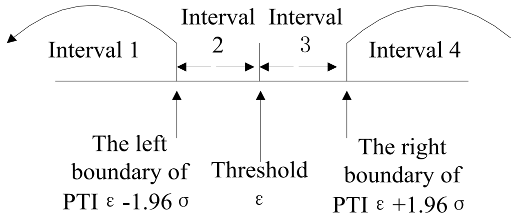

FIGURE 3. The probability threshold interval.

99.00% of the total area, respectively. We set the PTI to the interval $[\mu-1.96\sigma, \mu+1.96\sigma]$ as shown in Fig. 3.

In Fig. 3, we exchange the μ with the attribute threshold ε, Therefore, the PTI is $[\varepsilon-1.96\sigma, \varepsilon+1.96\sigma]$. The attribute values that fall into Interval 2 or Interval 3 need to be detected twice. This method focuses on correcting the decision errors to improve the decision accuracy based on the condition that the current attribute values cannot be completely correct. The DD method based on PTI is depicted in Fig. 4.

C. HANDOFF DECISION METHOD

We obtain the CNS through the selections made by the decision tree. Then, the proposed algorithm generates multiple-attribute decision values for each network in CNS and selects the network with the maximum multiple-attribute value as the target network to access. After normalizing the three attribute values in the decision tree, the multiple-attribute decision values are as follows:

$$H_i(x) = \frac{(RSS_i(x)-\varepsilon_i)^*}{\varepsilon_i}(1-P_i(\mathrm{FAP})(x)) * (1-P_i(\mathrm{MAP})(x))^*(1-BER_i(x))^*(1-P_{q_i}(x)), \tag{21}$$

where ε_i is the RSS threshold of network i, $P_i(\mathrm{FAP})(x)$ is the FAP of network i, $P_i(\mathrm{MAP})(x)$ is the MAP of network i and $P_{q_i}(x)$ is the blocking rate of network i. During the handoff execution phase, MT handoff occurs to the αth network in accordance with the following conditions:

$$H_\alpha(x) = \max\{H_1(x), H_2(x), \ldots, H_f(x)\}. \tag{22}$$

The α th network is the handoff target network. If the algorithm fails to generate the CNS, then it selects the network with the maximum RSS as the target network. If the target network is of the same type as the current network, a horizontal handoff occurs; otherwise, a vertical handoff occurs. If the target network is the network currently being accessed, the MT wills not handoff.

D. FEEDBACK COGNITIVE APPROACH

We obtain a knowledge base from data records related to the decision process in network handoffs. When the knowledge base is large enough, we can perform a statistical regression analysis mathematically. We assume that among large amounts of recorded data, the network attributes of the target network are subject to a Gaussian distribution. Therefore, we can obtain a Gaussian distribution function based on the

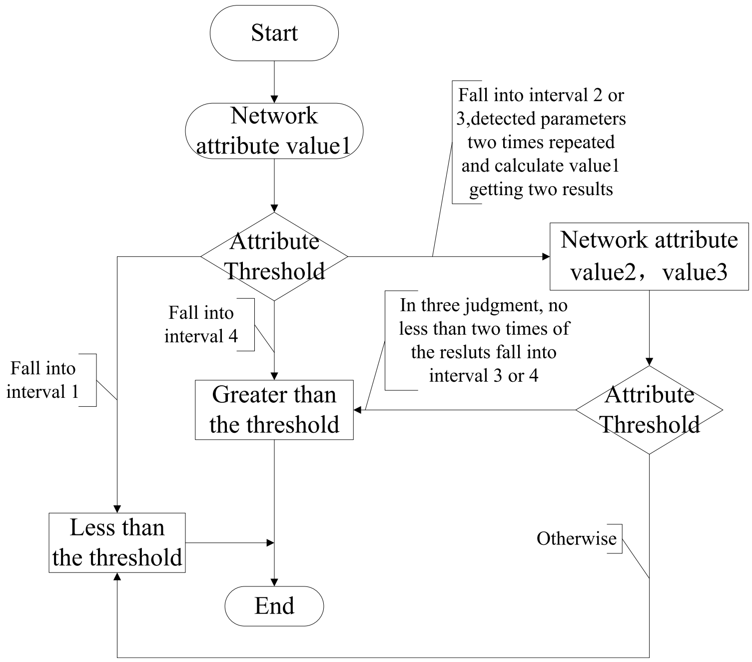

FIGURE 4. Dual-detection method based on PTI.

information in the knowledge base and set the decision tree thresholds using that feedback. Under the premise of not changing the handoff decision result, we can improve the thresholds and obtain a cleaner CNS. As the knowledge base grows, we would need to make continual revisions to obtain a more accurate regression function.

1) CONSTRUCTION OF KNOWLEDGE BASE

Every time the system executes a network handoff, some related data will be recorded. As this recorded data accumulates, we form the knowledge base. For example, after a network handoff, the set of recorded data is as follows:

$$\{CNSID, CNS\_NUM, TAR\_NETWORKID, RSS, BER, BR\}$$

Among these values, *CNSID* is a unique ID of the CNS at each handoff, and *CNS_NUM* indicates the number of networks in the CNS. *TAR_NETWORKID* denotes the target network, and *RSS*, *BER*, and *BR* are the attribute values of the target network.

2) REGRESSION ANALYSIS AND THRESHOLD UPDATE

This method is employed to update the RSS and BER thresholds. Taking RSS as an example, the RSS of the target network is subject to a Gaussian distribution with the parameters (μ, σ^2), and $X_1, X_2, \ldots, X_m$ is a sample of the target network's RSS from the knowledge base. $\bar{X}$ is the sample mean and S^2 is the sample variance. We obtain the following expressions:

$$S^2 = \frac{1}{w-1}\sum_{i=1}^{w}(X_i - \bar{X})^2 \tag{23}$$

$$E(\bar{X}) = \mu \tag{24}$$

$$E(S^2) = \sigma^2. \tag{25}$$

The probability that the handoff result will not change after resetting the threshold is P_ε. The threshold is reset to ε_r; therefore, the following constraints should be satisfied:

$$\begin{cases} 1 - P_\varepsilon < \Phi(\dfrac{\varepsilon_r - E(\bar{X})}{\sqrt{E(S^2)}}) \\ P_\varepsilon < 1 - \Phi(\dfrac{\varepsilon_1 - E(\bar{X})}{\sqrt{E(S^2)}}). \end{cases} \tag{26}$$

As the knowledge base grows, the algorithm constantly updates the RSS threshold. From a mathematical and statistical perspective, as the number of samples tends toward infinity, the results will eventually remain stable.

E. PERFORMANCE ANALYSIS OF THE ROBUST VERTICAL HANDOFF ALGORITHM BASED ON THE DECISION TREE

1) TIME AND SPACE COMPLEXITY ANALYSIS

First, we introduce an optimized mechanism for searching attributes that uses the TLB technology [27]. This mechanism can reduce the time complexity by increasing the space complexity and the system load at idle time. Reducing time complexity is more important than reducing space complexity given the capabilities of current computers.

This algorithm uses a Quick Search Table (QST) to optimize the attribute search process and store the network attributes values in advance. When a handoff is triggered, we first attempt retrieve the network attributes from the QST. If the desired network attributes are found in the QST, they can be used directly instead of performing the detection and calculation process. A sample of the complete network information recorded in QST is as follows:

$$\{NETWORKID, m-1, NOISE, ATTRIBUTE1, ATTRIBUTE2, ATTRIBUTE3, m, NOISE, ATTRIBUTE1, ATTRIBUTE2, ATTRIBUTE3\}$$

where *NETWORKID* refers to the name of the network, $m-1$ refers to last time period, *NOISE* denotes the interference intensity, and *ATTRIBUTE*1, *ATTRIBUTE*2, and *ATTRIBUTE*3 are the network attributes RSS, BER and BR, respectively. We need to maintain and update the data in the QST so that it does not become outdated. The vehicle terminal has sufficient power, so we update the QST data at a given interval. The specific rules for using and updating QST are as follows:

(1): If network parameter values have been stored, the attribute value at $m-1$ is regarded as the value at the last time period and the value at m is regarded as the value at the current time period.

(2): Detect the network parameter and update the data in QST at a given interval. For a given network, replace the value at $m-1$ with the value at m and replace the value at m with the newly detected value.

(3): A newly discovered network that has not yet been stored in the QST will be inserted into the QST.

(4): A network that can no longer be detected will be removed from the QST.

Next, we analyze the time and space overhead of the proposed algorithm and the traditional VHO algorithm based on decision tree. The time overhead to obtain RSS, interference intensity and the parameters for calculating BR are t_1, t_2, and t_3, respectively. The time overhead for calculating the attribute decision values of RSS, BER and BR are t_4, t_5 and t_6, respectively. The probability of satisfying the threshold at the RSS decision point is p_1 and at the BER decision point it is p_2. When the network handoff is triggered, the MT finds f available networks; however, f will not be a particularly large number and therefore, the time cost of generating target network in CNS is set to t_0. The time overhead of the traditional VHO algorithm (TT-VHO) during one handoff process is expressed as follow:

$$\begin{aligned} T_{\text{TT-VHO}} &= (t_1+t_4)+p_1(t_2+t_5+p_2(t_3+t_6))+t_0 \\ &= t_1+p_1t_2+p_1p_2t_3+t_4+p_1t_5+p_1p_2t_6+t_0. \end{aligned} \tag{27}$$

Searching the QST involves only an in-memory search, which occurs extremely quickly and can thus be neglected. The probabilities of attributes falling into the PTI among the three decision points are pr_1, pr_2 and pr_3, respectively. In the proposed algorithm (DT-VHO), the probabilities of satisfying the threshold at the RSS and BER decision points are po_1 and po_2, respectively. The time cost to calculate the five key expressions in the Kalman filter algorithm is linear and depends on the amount of data. Therefore, the time cost of generating the three filtered attributes can be set to δt_4, δt_5 and δt_6, respectively, where δ is a constant. Consequently, the time overhead of the proposed algorithm during one handoff can be expressed as follows:

$$\begin{aligned} &T_{\text{DT-VHO}} \\ &= (1-pr_1)\delta t_4+pr_1(2t_1+2\delta t_4)+po_1\{(1-pr_2)\delta t_5 \\ &\quad +pr_2(2t_2+2\delta t_5)+po_2[(1-pr_3)(t_3+\delta t_6) \\ &\quad +pr_3(2t_3+2\delta t_6)]\} \\ &= 2pr_1t_1+2po_1pr_2t_2+po_1po_2(1+pr_3)t_3+\delta(1+pr_1)t_4 \\ &\quad +\delta po_1(1+pr_2)t_5+\delta po_1po_2(1+pr_3)t_6+t_0. \end{aligned} \tag{28}$$

Only when the MT is far away from the access point will the network attributes fall into the PTI. Therefore, pr_1, pr_2 and pr_3 are generally small. According to Eqs. (27) and (28), the time complexity of the proposed algorithm increases linearly compared to the TT-VHO algorithm; generally, however, both algorithms have the same time complexity.

$$O(T_{\text{DT-VHO}}) = O(T_{\text{TT-VHO}}) \tag{29}$$

Assuming the QST contains information for N networks, the data in the QST will be updated M times in each time unit. This task requires $MN(t_1+t_2+\delta t_5+\delta t_6)$ and occurs at system idle times. Because swapping data in memory takes little time, we can ignore the time cost of an increase in updated network information at the time period $m-1$ with the network information acquired at time period m.

Because the QST is stored in memory and uses double type data to store each item of network information, the space consumed is $10N{*}sizeof(\text{double})$, where $sizeof(\text{double})$ is the memory size required for double type data in the computer (the exact size is based on the operating system and programming language). In the worst case (all three decision values fall into PTI), the memory space consumed by the proposed algorithm during the handoff execution phase must store two extra sets of data compared to the TT-VHO algorithm. This situation is well within the acceptable limits for current computer systems.

2) ANALYSIS ON ERROR HANDOFF DECISION PROBABILITY

Typically, when the attribute's deviation is σ_0 and the noise deviation of the attribute value in current moment is σ_L, according to the Kalman filter algorithm, the attribute deviation after a single filtering operation is

$$\begin{cases} \sigma_{\text{cur}} = \sqrt{\dfrac{\sigma_0^2}{\sigma_0^2+\sigma_L^2}} * \sigma_L \\ \dfrac{\sigma_{\text{cur}}}{\sigma_0} = \sqrt{\dfrac{\sigma_L^2}{\sigma_L^2+\sigma_0^2}} < 1. \end{cases} \tag{30}$$

From Eq. (30), the attribute deviation becomes lower: σ_{cur} becomes smaller as the number of iterations increases. We can obtain the decision error probability after filtering by substituting σ_{cur} into Eqs. (7), (8), (15), and (16).

Let P_{eror} be the decision error probability at the decision point. The decision error probability differs according to different PTI sizes. Consider the interval size $[\mu - 1.96\sigma, \mu + 1.96\sigma]$ as an example. From a theoretical and statistical perspective, the decision error can be detected with a probability of 95%. In our proposed algorithm, the DD method based on PTI has a certain probability of correcting the decision error. To analyze the probability of error correction, we set the true value of the attribute to v. Then, the probability of error correction when the attribute value falls into PTI is

$$P_{\text{redress}} = (1 - \Phi(\frac{-|\varepsilon - v|}{\sigma_{\text{cur}}}))^2, \tag{31}$$

where ε is the threshold of the attribute value. For all decision errors, the probability of error correction is $0.95^* P_{\text{redress}}$. On the other hand, the probabilities of decision errors in the TT-VHO algorithm and DT-VHO algorithm, respectively, are

$$P_{\text{TT}-\text{VHO}} = \Phi(\frac{-|\varepsilon - v|}{\sigma_0}) \tag{32}$$

$$\begin{aligned} P_{\text{DT-VHO}} &= \Phi(\frac{-|\varepsilon - v|}{\sigma_{\text{cur}}})^*(1 - 0.95P_{\text{redress}}) \\ &= 0.95\Phi(\frac{-|\varepsilon - v|}{\sigma_{\text{cur}}})^*(1 - \Phi(\frac{-|\varepsilon - v|}{\sigma_{\text{cur}}}))^2. \end{aligned} \tag{33}$$

According to Eqs. (32) and (33), we can obtain

$$\left\{ \begin{array}{l} \Phi(\frac{-|\varepsilon - v|}{\sigma_{\text{cur}}}) < \Phi(\frac{-|\varepsilon - v|}{\sigma_0}) \\ (1 - \Phi(\frac{-|\varepsilon - v|}{\sigma_{\text{cur}}}))^2 < 1 \end{array} \right\} \Rightarrow P_{\text{DT-VHO}} < P_{\text{TT-VHO}}. \tag{34}$$

Eq. (34) shows that the decision error probability of the DT-VHO algorithm is less than that of the TT-VHO algorithm. In addition, the decrement of the decision error probability is

$$\begin{aligned} &P_{\text{TT-VHO}} - P_{\text{DT-VHO}} \\ &= \Phi(\frac{-|\varepsilon - v|}{\sigma_0}) - 0.95\Phi(\frac{-|\varepsilon - v|\sqrt{\sigma_L^2 + \sigma_0^2}}{\sigma_L^* \sigma_0}) \\ &\quad * (1 - \Phi(\frac{-|\varepsilon - v|\sqrt{\sigma_L^2 + \sigma_0^2}}{\sigma_L^* \sigma_0}))^2 > 0. \end{aligned} \tag{35}$$

IV. SIMULATION RESULTS AND ANALYSIS

In this section, we present simulations to illustrate the benefits of our proposed algorithm. We compare the proposed algorithm (DT-VHO) with the VHO algorithm based on fuzzy logic (FL-VHO) [10] and the traditional VHO algorithm based on the decision tree (TT-VHO) [23]. We denote the DT-VHO1 algorithm as our proposed algorithm, which uses only the Kalman filter to improve the decision accuracy.

A. SIMULATION SETUP

We build a heterogeneous vehicle network model that includes LTE, WIMAX, and an ad hoc network using WAVE. Each network is fixedly distributed in a rectangular area $20km \times 20km$, the network and MTs position are given in two-dimensional coordinates. The LTE1 network coordinates are (4012, 16010), the LTE2 network coordinates are (15223, 11000), the LTE3 network coordinates are (13950, 1660), the WIMAX1 network coordinates are (3130, 13205), the WIMAX2 network coordinates are (16860, 1500), and the center point of the WAVE network coordinate is (11023, 9861). Orthogonal Frequency Division Multiplexing (OFDM) technology is used in the wireless access network. The whole scenario is under the full coverage of LTE base stations. The simulation scenario is shown in Fig. 5 and the simulation parameters are shown in Tab. 1.

TABLE 1. Network simulation parameters.

Network	Transmission power ρ	Path loss factor η	Noise bias σ_1	Covering radius r	Access bandwidth w
LTE	30dBm	33dBm	6dBm	Full coverage	2Mbit/s
WIMAX	25dBm	35dBm	8dBm	10km	45Mbit/s
WAVE	Constant signal strength, set to −95dBm			5km	27Mbit/s
Other parameter settings, RSS threshold $\varepsilon_1 = -110dBm$, BER threshold $\varepsilon_2 = 0.006$, BR threshold $\varepsilon_2 = 0.07$. Interference signal strength					
$D(x) = -130 + u(x)$dBm, $u(x)$ subject to Gaussian random distribution with the parameters $(0,10)$, the MT maintains a constant speed of 60 km/h.					

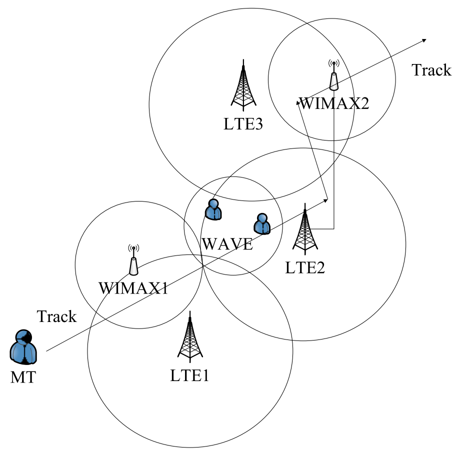

FIGURE 5. Heterogeneous vehicle network simulation scenarios.

B. SIMULATION RESULTS

1) ANALYSIS OF THE DECISION ACCURACY

The decision accuracy has a direct impact on handoff performance. A decision error is always followed immediately by a second handoff immediately; otherwise, the MT's QoS cannot be guaranteed. In addition, in extreme cases, increasing the number of handoffs may cause a ping-pong effect.

Figs. 6 and 7 show the times that a given network enters the CNS and how that number changes according to the changing distance between the MT and the access point. The optimal curves in Fig. 6 and Fig. 7 represent the times that a given network enters the CNS with no noise. The curves for TT-VHO-FAN and TT-VHO-MAN represent the same numbers of false alarm and missed alarm conditions, respectively. The figures show that the times that a given

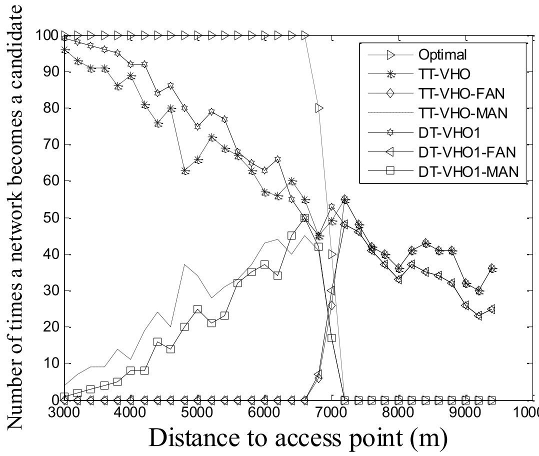

FIGURE 6. Times that a given network enters the CNS (Kalman filter).

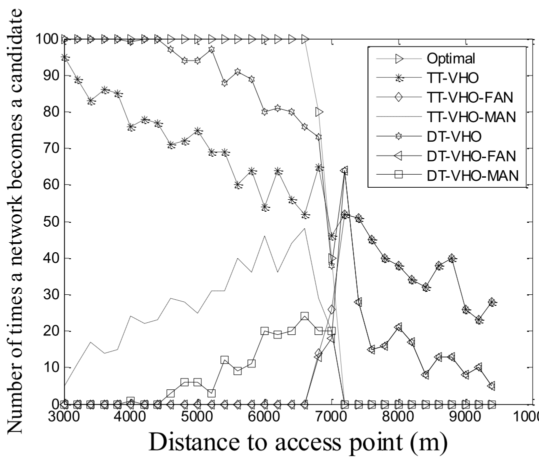

FIGURE 7. Times that a given network enters the CNS (Kalman filter and DD).

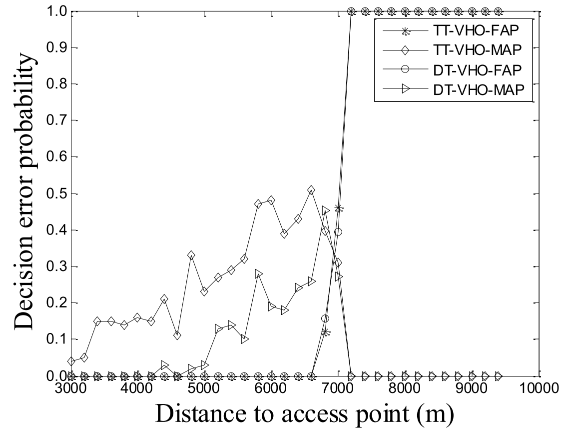

FIGURE 8. The Probability of decision error.

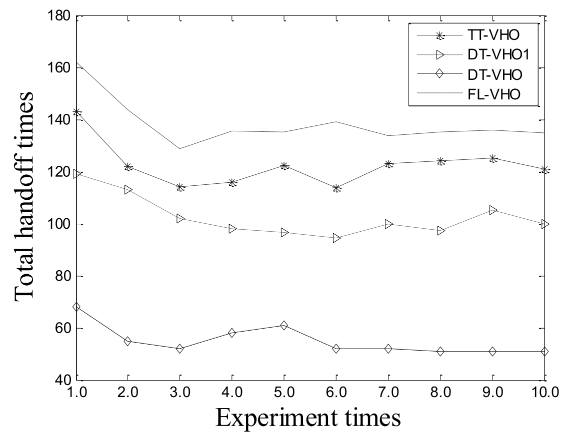

FIGURE 9. The total handoff times for a mobile terminal.

network enters the CNS in DT-VHO1 are higher than the number in TT-VHO, but lower than the number in Optimal. Furthermore, the numbers of false alarms and missed alarms in DT-VHO1 are lower than those in TT-VHO. When the MT is close to an access point, only missed alarms can occur, and the number of missed alarms increases gradually as the MT's distance from the access point increases. The number of missed alarms becomes 0 after the distance reaches a certain point (between 6,000 and 7,000 m). Meanwhile, the number of false alarms first gradually increases and then decreases as the distance continues to increase. This result occurs because when the MT is close to an access point, the RSS is high and the noise is weak; consequently, the wrong decisions are only missed alarms. At greater distances, when the RSS is poor and the noise is strong, the number of missed alarms will increase. In contrast, false alarms occur only after the distance reaches a certain point. As the distance continues to increase, all the wrong decisions become false alarms.

Fig. 7 shows that using the proposed optimization methods in the DT-VHO algorithm enhances the decision accuracy. The general trend of the curve in Fig. 7 is similar to that in Fig. 6, but the DT-VHO algorithm further improves the decision accuracy compared to the DT-VHO1 algorithm in terms of false alarms and missed alarms.

Fig. 8 illustrates the changes in the false alarm and missed alarm probabilities as the distance between an MT and the access point increases. Both represent false decisions made at a network attribute decision point. The false alarm and missed alarm probabilities that occur when using the DT-VHO algorithm are lower than those that occur when using the TT-VHO algorithm. When the distance exceeds 7000 meters, all the decision errors become false alarms, and the missed alarm error rate falls to 0.

2) ANALYSIS OF HANDOFF TIMES AND HANDOFF FAILURE RATE

The network handoff time reflects the stability of the handoff algorithm. Larger handoffs times increase the overhead, and a ping-pong effect leads to a decline in the MTs' QoS. Fig. 9 shows that the DT-VHO1 algorithm reduces the handoff times compared to the TT-VHO algorithm and that the DT-VHO algorithm reduces the handoff times more than the DT-VHO1 algorithm. This result occurs because the DT-VHO algorithm adopts both the Kalman filter and the DD method based on PTI; therefore, it can obtain more

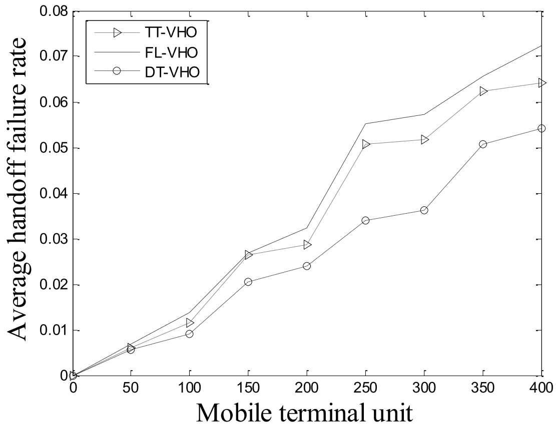

FIGURE 10. The average handoff failure rate.

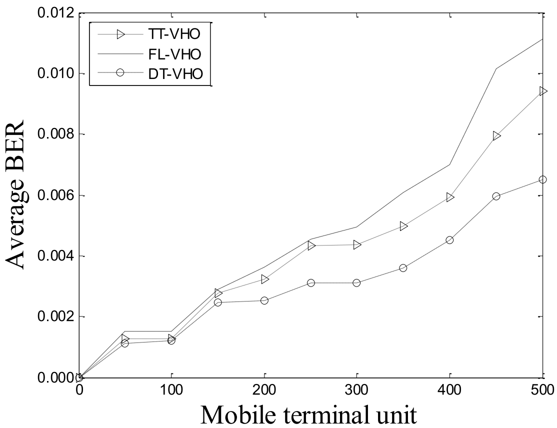

FIGURE 11. Average BER of wireless networks.

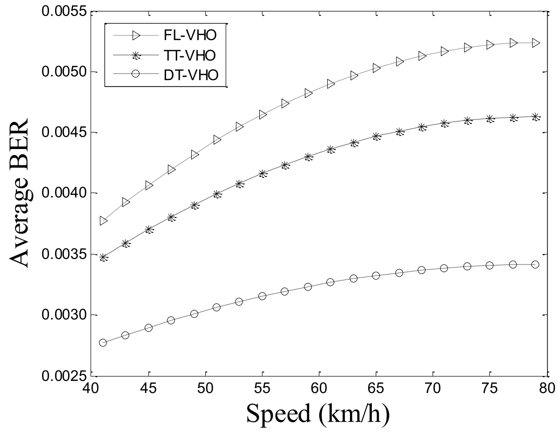

FIGURE 12. Average BER at various terminal speeds.

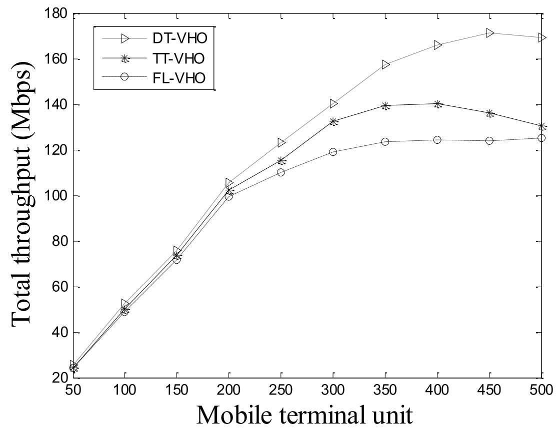

FIGURE 13. Network total throughput.

accurate network attributes and correct some decision errors, enhancing the decision accuracy. Consequently, the MT is handed off to the network with the best QoS.

When the handoff fails, the MT's network connection will be interrupted and it will be unable to transfer data. The handoff failure rate is the probability that the times of failed handoffs account for the total handoff times. The simulation in Fig. 10 shows that the three algorithms all have a low handoff failure rate when the number of MTs is small and that the handoff failure rate rises with as the number of MTs increases. Among the three algorithms, the DT-VHO algorithm has the lowest handoff failure rate because it reduces the number of connection interruptions caused by decision errors.

3) ANALYSIS OF BIT ERROR RATE AND TOTAL THROUGHPUT

BER reflects the ratio of the number of bit errors to the total transmission bit volume in a given time unit. The throughput is the data volume that the network can transmit successfully in a time unit. Consequently, improving network throughput and reducing the BER can improve network data transmission performance.

Fig. 11 compares the average BER among the three algorithms, TT-VHO, FL-VHO, and DT-VHO, as the number of MTs increases. When the number of MTs is below 100, the BER values of all three algorithms remain low. This occurs because the network capacity is not saturated. As the number of MTs increases, the average BER values of the three algorithms all gradually increase, but DT-VHO has the lowest BER. When the number of MTs reaches 450 or higher, DT-VHO will have a BER higher than the threshold. At this point, the network load is heavy, and there is a possibility that the CNS may not be generated successfully; consequently, the MTs begin switching to the network with the maximum RSS. Because the average BER is a statistical value, the proposed DT-VHO algorithm generally outperforms the other two algorithms.

In heterogeneous vehicle networks, the speeds of the MTs vary over a certain range along different roads. In Fig. 12, we set the number of MTs to 300, and the MTs' speeds change from 40 km/h to 80 km/h. The simulation results show that the BER rises as the terminal's speed increases and that the DT-VHO algorithm maintains the lowest BER of the three algorithms. Therefore, the DT-VHO algorithm adapts better to terminal speed changes in heterogeneous vehicle networks.

Fig. 13 compares the total throughput among the three algorithms under different numbers of MTs. The simulation results show that the DT-VHO algorithm improves total network throughput. Similar to the previous experiment, we set

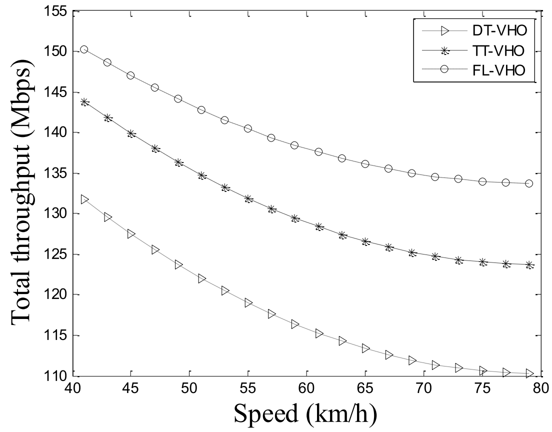

FIGURE 14. Network total throughput.

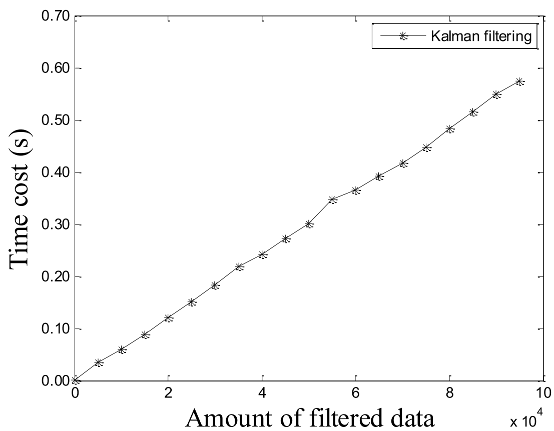

FIGURE 15. Time overhead of the Kalman filtering algorithm.

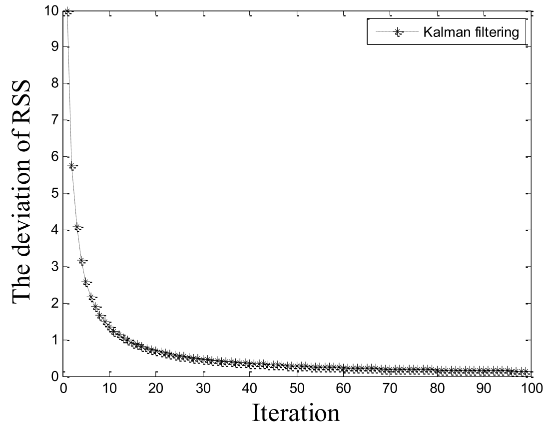

FIGURE 16. The deviation of parameter.

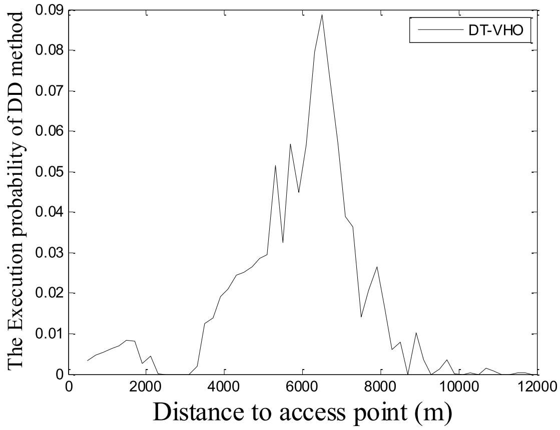

FIGURE 17. Execution probability of DD method based on PTI.

the number of MTs to 300 (Fig. 14) and tested the total network throughput at different terminal speeds. The DT-VHO algorithm achieves the best performance in total network throughput when the MTs are moving at different speeds.

4) ANALYSIS OF ALGORITHM'S TIME COST

The time cost of an algorithm is an important index when evaluating the effectiveness of the algorithm. Our proposed DT-VHO algorithm uses two methods to enhance the decision accuracy. The Kalman filtering algorithm has a linear time complexity, and the time complexity of the DD method based on PTI is related to the probability and statistical factors. To verify the theoretical analysis of the algorithm time complexity, we designed the following experiments. As shown in Fig. 15, we tested the time cost of the Kalman filtering algorithm by filtering increasing amounts of data. These experiments were conducted in the MATLAB 2012 programming environment on a computer running a Windows 7 64-bit operating system with an Intel(R) Pentium(R) dual core processor at 3.50 GHZ and 8 GB of RAM.

Fig. 15 shows that the time cost of the Kalman filtering algorithm varies linearly with the amount of data. In addition, we found that the time cost to process 100,000 sets of data is approximately 2.5 s, so we can estimate the time cost of processing a single set of data. When the iterative data filtering process is repeated using the same procedure, the time cost is equivalent to that required to process a new set of data. In Fig. 16 we show the relationship between the parameter deviation and the number of iterations required by the Kalman filter algorithm. After the filtering operation, the parameter deviation is only approximately 0.58 times the original value after 10 iterations; in other words, the parameter deviation value is greatly reduced. In practical applications, the number of networks available to an MT is limited, and the number of parameters considered by the algorithm is 3. It can be concluded that using the Kalman filtering algorithm is feasible for improving parameter value accuracy from a time cost perspective.

In Figs. 17 and 18, we repeated the experiment 10,000 times and then used the average experimental results because the time cost of the proposed algorithm is a statistical value. From Fig. 17, we can see that the probability of the DD method based on PTI is generally low. Therefore, the time cost of the proposed algorithm does not increase much by using this method. When the distance from the access point is between 5,000 and 8,000 meters, the probability of executing the method becomes relatively large due because the attributes are near the threshold and have a greater

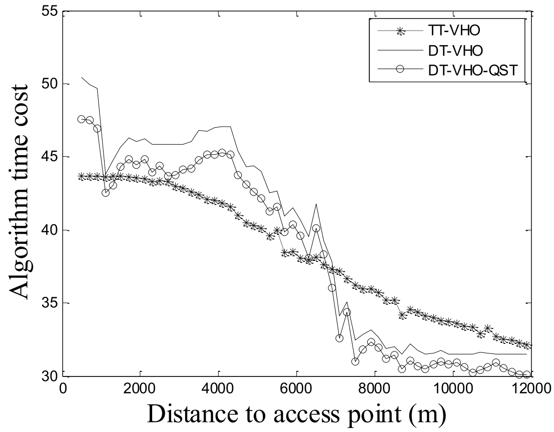

FIGURE 18. Overall time overhead of the algorithm.

probability of falling into the PTI. Fig. 18 shows the results of comparing the proposed algorithm with the TT-VHO algorithm regarding time overhead. The DT-VHO-QST algorithm is the proposed algorithm using the QST mechanism. Overall, when the terminals are relatively close to the access point, the proposed algorithm's time cost is higher than that of the traditional algorithm, largely because the filtering process and the DD method increase time cost. However, when the MT is far from the access point, the time cost of the proposed algorithm is less than that of the traditional algorithm. This result is related to the decision-making process of the algorithm. At greater distances, the probability that the RSS will not meet the threshold increases and the probability of the decision-making process along the decision tree decreases. The proposed algorithm reduces the probability of the decision-making process along the decision tree in the event of a decision error, which reflects a lower overall time cost. On the other hand, the curve of the DT-VHO-QST algorithm in Fig. 18 shows that the QST mechanism reduces the time cost of the algorithm due to the higher speed of parameter value lookups.

These simulation results verify the theoretical analysis of the algorithm's time complexity; the proposed algorithm and the traditional algorithm have the same order of time complexity.

V. CONCLUSIONS

In this paper, we proposed a robust VHO algorithm based on the decision tree. This algorithm is suitable for the network handoff problem of high-speed users (mobile terminals) in heterogeneous wireless networks. We proposed using the Kalman filter algorithm to obtain more accurate network attribute values, and we designed a dual-detection method based on PTI to correct decision errors. We introduced the use of the TLB technology used in operating systems to establish a fast searchable table containing network information. This approach reduced the algorithm's time cost, but it is applicable only to terminals with an adequate power supply. The results of experiments show that the proposed algorithm can improve both the accuracy of handoff decisions and the total network throughput while reducing the ping-pong effect and ensuring the QoS of mobile terminals in heterogeneous wireless networks.

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BIN MA received the Ph.D. degree in computer science and technology from Chongqing University, Chongqing, China, in 2015.

He is currently a Professor with the Chongqing University of Posts and Telecommunications, Chongqing. His recent work focuses on spectrum handover in cognitive radio networks and vertical handoffs in heterogeneous wireless networks.

DONG WANG received the B.S. degree from the Chongqing University of Posts and Telecommunications, Chongqing, China, in 2015, where he is currently pursuing the M.S. degree in computer science and technology.

His research interests include vertical handoffs in heterogeneous wireless networks and cognitive radio.

SHUANGGUO CHENG received the B.S. degree in 2015. He is currently pursuing the M.S. degree with the Chongqing University of Posts and Telecommunications, Chongqing, China.

His research interests include cognitive radio and heterogeneous networks.

XIANZHONG XIE received the Ph.D. degree in communication and information systems from Xidian University, Xi'an, China, in 2000.

He is currently with the School of Computer Science and Technology, Chongqing University of Posts and Technology, Chongqing, China, as a Professor and the Director of the Institute of Broadband Access Technologies. His research interests include cognitive radio networks, multiple-input-multiple-output systems, and wireless communications.