Two-Dimensional Behavior-Marker-Based Data Forwarding Incentive Scheme for Fog-Computing-Based SIoVs

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***Abstract*—In social Internet of Vehicles (SIoVs), vehicles can usually act as data-relaying nodes to forward data. However, vehicle nodes often show their personal and social selfishness in data forwarding (namely vehicle nodes are not willing to forward data), whose selfishness greatly influences the delivery ratio of data forwarding. In this article, we propose a 2-D behavior-marker-based data-forwarding incentive scheme to motivate vehicle nodes to participate in data forwarding in fog-computing-based SIoVs. First, we design a 2-D behavior marker mechanism, which can be used to completely evaluate vehicle nodes. Second, we construct a currency credit-based data-forwarding incentive strategy based on the 2-D marker and the social attributes of vehicle nodes, which is used to deal with vehicular normal behavior, vehicular selfish behavior, and vehicular malicious behavior. Compared with other related schemes, our proposed scheme can completely evaluate the behaviors of vehicle nodes and can further promote the cooperation of data-forwarding between selfish nodes. The experimental results show that our scheme is more efficient and stable in data forwarding in fog-computing-based SIoVs.**

***Index Terms*—Data forwarding, fog computing, incentive strategy, social attribute, social Internet of Vehicles (SIoVs).**

NOMENCLATURE

F	Interest table.
ST	Forwarded data's sequence table.
RT	Received data's sequence table.
Re_C	Fog-based high-level 2-D behavior marker.
Re_C^*	Node-based low-level 2-D behavior marker.
Is	High-level data-forwarding preference ratio.
Rv	High-level data-forwarding real ratio.
Is^*	Low-level data-forwarding preference ratio.
Rv^*	Low-level data-forwarding real ratio.
$E\_I_{(i,j)}(N)$	Social relationship between vehicle nodes.
$s_{i,j}$	Data sequence forwarded by node i to node j.
$r_{i,j}$	Data sequence received by node i to node j.
τ	Update interval for fog-based 2-D behavior marker.
θ	Ratio of social relationship between vehicle nodes.
L	Size of data.
B	Buffer size of node.
B_t	Buffer size of node at t time.
ttl	Current remaining time to live of data.
TTL	Time to live of data.

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I. INTRODUCTION

A. Background

WITH the development of social networks, mobile social networks and internet of vehicles are gradually combined to form social Internet of Vehicles (SIoVs) [1], [2]. In SIoVs, vehicles can share their social data based on social relationships, where social relationships can be established during vehicle travel. For example, a group of vehicles may have common interests, preferences, or demands when they move on the roads where their driving time and location can be close. In order to share interesting data, vehicles have an important function to act as data-relaying nodes to forward data [3], [4]. Therefore, some social-based data-forwarding strategies can identify vehicle nodes with similar social attributes so as to efficiently forward data. Vehicle behaviors are usually considered as full collaboration of data forwarding in some social-based data-forwarding strategies, which do not consider node selfishness. However, in the real world, vehicle nodes may hope to obtain more external resources while protecting or saving their own resources, so as to eventually form node selfishness. Obviously, node selfishness can hinder the cooperation of data forwarding between vehicle nodes, which seriously influences user experience and network performance. Then, according to the behaviors of vehicle nodes, vehicles can be divided into normal nodes, selfish nodes, and malicious nodes. Normal nodes actively participate in data forwarding, which are considered as full cooperation. Selfish and malicious nodes are considered to lack active participation in data forwarding or even refuse to

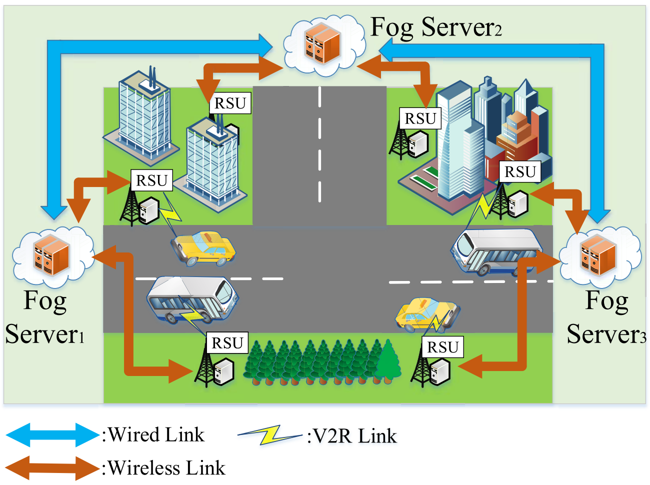

Fig. 1. Fog-computing-based SIoVs.

participate in data forwarding, so these nodes can influence the delivery ratio of data forwarding [5], [6].

Currently, the concept of vehicular fog computing (VFC) has been proposed [7]–[11], which can directly acquire, process, and store traffic data at the edge of the vehicle network. The architecture of fog computing is introduced into SIoVs, as shown in Fig. 1. In fog-computing-based SIoVs, each fog server can directly obtain traffic and vehicular data within its managing area through its connected road side unit (RSU) in real time; furthermore, the fog servers can also exchange their traffic and vehicular data timely. Additionally, each vehicle is regarded as a mobile intelligent device (fog node) with multi-sensors [such as on board unit (OBU)], which has certain computing and communication ability to process data.

Presently, many data-forwarding schemes are based on the full cooperation of vehicle nodes in SIoVs, which have the weak ability to solve node selfishness. So, some data-forwarding schemes are proposed to reduce the negative influence of node selfishness through selfish node detection and node incentive mechanism. For example, some selfish node detection schemes employ the watchdog system to accurately distinguish whether a node is selfish or not. However, although the proposed watchdog system can effectively detect the selfish nodes, it does not construct the reward and punishment strategy for the selfish nodes, so as to alleviate the selfish behavior of vehicle nodes. Furthermore, some node incentive mechanisms are proposed to activate vehicle nodes to forward data, which are mainly divided to virtual currency-based incentive strategy, credit-based incentive strategy, tit-for-tat (TFT) incentive strategy, and so on. These node incentive schemes can effectively encourage vehicle nodes to participate in data forwarding and improve the delivery ratio of data forwarding. However, these incentive schemes lack the overall evaluation of node selfishness. Although there are some node incentive schemes in which multiple vehicle nodes may evaluate the selfishness of other nodes, these related schemes still have some limitations.

B. Our Contributions

In this article, we propose a 2-D behavior-marker-based data-forwarding incentive scheme for fog-computing-based SIoVs, which can motivate vehicle nodes to participate in data forwarding. Our proposed scheme not only employs the vehicular social attributes to improve the data delivery ratio, but also combines the 2-D behavior marker and the currency credit-based incentive strategy to reduce the effect of malicious nodes and encourage the normal and selfish nodes to participate in data forwarding. Our main contributions are as follows.

1) We propose a 2-D behavior marker model to evaluate the forwarding capability, selfishness, and malicious tendency of vehicle nodes. First, we consider normal loss of data packets where data packets are not forwarded to destination nodes. Second, we construct the 2-D behavior marker model to protect the data-forwarding revenue mechanism against selfish and malicious behaviors of vehicle nodes, which is further divided into the fog-based high-level behavior marker and the node-based low-level behavior marker.
2) We propose a currency credit-based incentive strategy based on the 2-D behavior marker, which is used to deal with vehicular normal behavior, vehicular selfish behavior, and vehicular malicious behavior. In our strategy, the data-forwarding procedure is defined as a transaction process, where the transaction parties not only need to know each other's offer, but also need to inform their own income status and 2-D behavior marker so as to evaluate their data-forwarding preference and malicious tendency.
3) We propose a 2-D behavior-marker-based data-forwarding incentive scheme in fog-computing-based SIoVs. Our proposed scheme combines the 2-D behavior marker and the currency credit-based incentive strategy to encourage vehicle nodes to participate in data forwarding and reduce node reward to punish selfish and malicious nodes.
4) We make experiments to evaluate and analyze the performance of our proposed scheme. In the experiments, we mainly evaluate the successful ratio of data delivery generated by our scheme under different ratios of selfish and malicious nodes, different TTLs, and different buffer sizes. Furthermore, we compare our scheme with some related schemes. The experimental results show that our scheme is superior and more stable than other related schemes.

C. Organization

The rest of the article is organized as follows. In Section II, we review the related works about data forwarding. In Section III, we propose a 2-D behavior-marker-based data-forwarding incentive scheme for fog-computing-based SIoVs. In Section V, we make some experiments to test and evaluate the performance of our scheme. Finally, we draw our conclusions in Section VI.

II. Related Work

At present, many data-forwarding schemes do not consider node selfishness in SIoVs. To solve the problem of node selfishness, selfish node detection and node incentive mechanism are introduced into the data-forwarding schemes. Based on selfish node detection, some schemes employ the watchdog system to distinguish whether a node is selfish or not. Dias *et al.* [12] proposed a collaborative watchdog system to detect bad behaviors of vehicle nodes so as to reduce their influence on overall network performance. Their scheme depends on the cooperative exchange of node reputation. Jedari *et al.* [13] proposed a social-based watchdog system (SoWatch), where the watchdog node is used to analyze the social relationship information of its encounter node and identify whether this node has selfish behavior during data forwarding. Furthermore, the watchdog node can receive the second-hand watchdog messages from other watchdog nodes so as to improve the detection time and accuracy. Based on node incentive mechanism, Rehman *et al.* [14] proposed an incentive scheme called as IPS. Their scheme elects the high-weight cooperative vehicle nodes as supervisors to evaluate whether a vehicle node is selfish or not, and the Vickrey-Clarke–Groves (VCG) model is employed to check the weights of these supervisors. Chen *et al.* [15] also proposed a novel incentive scheme called Multicent, which uses game theory to encourage vehicle nodes to follow cooperation. Ma and Wang [16] proposed a cooperative incentive mechanism based on game theory. Their scheme provides data-forwarding services for vehicle nodes and provides different amounts of rewards or costs according to priority values obtained by forwarding other data. Chhabra *et al.* [17] proposed a data-routing protocol, which reduces node computational consumption and motivate nodes to participate in data routing. Their scheme is based on the Stackelberg game theory to motivate relay nodes by calculating the best reward. Their scheme can eliminate node selfishness and improve the successful ratio of data delivery. Buttyn *et al.* [18] proposed a TFT-based incentive scheme. In their scheme, after vehicle nodes exchange or forward their messages, vehicle nodes can download the same amount of messages from other nodes. Zhou *et al.* [19] proposed an incentive-driven and freshness-aware content dissemination scheme. Their scheme uses TFT to deal with the selfish behavior of nodes and proposes a content exchange protocol, which determines whether to exchange content according to the usefulness of content. Shivshankar and Jamalipour [20] proposed a game-theoretic strategy for enhancing group cooperation in vehicular ad hoc networks (VANETs). Their scheme employs the conditional TFT and unconditional altruism strategies to enhance cooperation among nodes. Rajput and Banerjee [21] proposed a mathematical modeling method for VANETs. In their scheme, the probability by which a particular vehicular node would accept the relay request of other vehicular nodes can be calculated by combining the available degree of resource and the resilient reciprocating strategy. Seregina *et al.* [22] proposed a data-forwarding scheme for two-hop delay tolerant networks, where the source node wishes to deliver its message to the destination node as soon as possible and promises that each relay node can be rewarded. Li and Wu [23] proposed a secure incentive scheme to stimulate the data-forwarding cooperation in VANETs, which provides the weighted reward for vehicle nodes to ensure the fairness of obtaining reward. Lu *et al.* [24] also proposed a practical incentive scheme, in which the source node sends its data with the incentive information to the destination node. By providing the fairness of incentives, their scheme can stimulate selfish nodes to help forward data so as to obtain the better performance of data delivery.

Additionally, according to virtual currency-based incentive mechanism, Zhang and Bai [25] introduced the transmission method of interest packets and data packets and further proposed a routing incentive strategy based on virtual credit and a secure data transmission mechanism. Liu *et al.* [26] proposed a reverse auction incentive mechanism, which provides a donation compensation method to increase the transmission participation rate of spare vehicle nodes. Han *et al.* [27] proposed an incentive scheme based on dynamic pricing, which stimulates content sharing in vehicular networks by jointly considering content information and link status. Wu *et al.* [28] proposed a node incentive strategy based on overdraft virtual currency mechanism. In their scheme, the proposed overdraft virtual currency mechanism can virtualize the node data-forwarding ability as the overdraft voucher to ensure that the data-forwarding transaction can be completed when the virtual currency of a node is insufficient.

Furthermore, because some vehicle networking applications require high computing costs and vehicular computing resources are limited, many researchers have proposed to combine vehicle networking and fog computing to VFC [2]. The framework of VFC can provide strong computing ability to accomplish computing tasks with higher efficiency. In the VFC framework, vehicles and mobile devices are both regarded as fog nodes, which can transfer data from one place to another place by multi-hop based on mobile characteristics of vehicles [3].

III. Two-Dimensional Behavior-Marker-Based Data-Forwarding Incentive Scheme for Fog-Computing-Based SIoVs

In the section, we propose a 2-D behavior-marker-based data-forwarding incentive scheme for fog-computing-based SIoVs. In our proposed scheme, each fog server manages multiple RSUs, and each RSU is responsible for managing the vehicles in its management area. Furthermore, these fog servers are able to cooperative to communicate with each other. Our proposed scheme combines the 2-D behavior marker and the currency credit-based incentive strategy to encourage vehicle nodes to participate in data forwarding. First, we construct the fog-based high-level behavior marker and the node-based low-level behavior marker according to the location of vehicle nodes, which are used to evaluate the selfishness and malicious tendency of vehicle nodes. Second, we combine the behavior marker and the currency credit-based incentive strategy to reduce node reward to punish selfish and malicious nodes. Additionally, the social attributes of

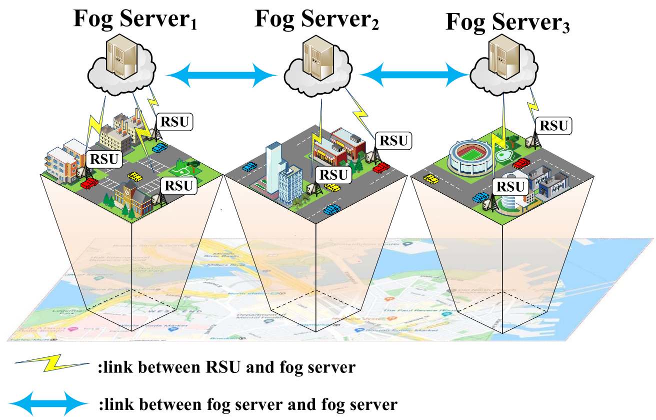

Fig. 2. Node social interaction framework in fog-computing-based SIoVs.

vehicle nodes are added to the incentive method, which are used to accurately evaluate the forwarding price of vehicle nodes. The related symbols in our scheme are described in Nomenclature.

A. Node Social Interaction Model in Fog-Computing-Based SIoVs

In the section, we propose a node social interaction model based on multi-feature of vehicle in fog-computing-based SIoVs, as shown in Fig. 2. In our scheme, each vehicle is equipped with OBU, and thus each vehicle can communicate with nearby RSUs timely; each RSU is the middle communication entity to connect vehicle node and fog server; furthermore, each fog server is responsible for collecting and updating the behavior marker information of each vehicle node regularly, where the fog servers can share their obtained information with each other.

1) Vehicle Node Model: In the section, we define three types of vehicle node: normal node, selfish node, and malicious node. Selfish nodes are embodied in personal selfishness and social selfishness, which are characterized by receiving and forwarding preference for different types of data. So, selfish nodes only forward some preferred categories of data. Malicious nodes do not follow the rules of forwarding strategy to forward data, and maliciously abandon received data. Additionally, all vehicle nodes must register their identity information to the fog servers.

In our scheme, each node carries its interest table, forwarded data identification table, received data identification table, and 2-D behavior marker. The related symbols are described as follows. $F_i = \{f_{i,1}, f_{i,2}, \ldots, f_{i,k}\}$ denotes the interest table of the ith node, where $f_{i,k}$ is the kth interest of the ith node. $\mathrm{ST}_i = \{s_{i,1}, s_{i,2}, \ldots, s_{i,n}\}$ denotes the forwarded data identification table of the ith node, which records the identifications of forwarded data. Furthermore, $s_{i,j} = \{m_1, m_2, \ldots, m_g, \ldots\}$ is a data identification sequence that the node i forward to the node j, where $1 < j < n$ and n is the number of encountered vehicle nodes; m_g denotes the identification of the gth data, which contains the identifier, source node name, and destination node name of the gth data. $\mathrm{RT}_i = \{r_{i,1}, r_{i,2}, \ldots, r_{i,n}\}$

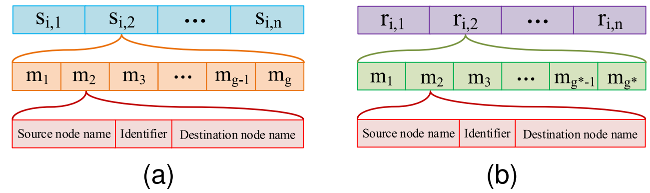

Fig. 3. Structure of ST_i and RT_i. (a) Table ST_i. (b) Table RT_i.

denotes the received data identification table of the ith node, which records the identifications of received data by its buffer (including received historical data information). Also, $r_{i,j} = \{m_1, m_2, \ldots, m_{g^*}\}$ is a data identification sequence that the node i receives from the node j, where $1 < j < n$ and n is the number of encountered nodes; m_{g^*} denotes the identification of the g^*th data, which contains the identifier, source node name, and destination node name of the g^*th data. The structure of the tables ST_i and RT_i is shown in Fig. 3, where Fig. 3(a) shows the table ST_i and Fig. 3(b) shows the table RT_i.[1] $Re\_C_i = (Is, Rv)$ denotes the 2-D behavior marker of the ith node, where Is is the high-level data-forwarding preference ratio of the node and Rv is the high-level data-forwarding real ratio of the node. The 2-D behavior marker of the node is described in detail in Section III-B.

2) SIoVs Model: In the section, we construct a multi-feature-based SIoVs model according to the privacy-preserving interest-based forwarding (PRIF) strategy [29], where the PRIF data-forwarding strategy is a single-feature-based data-forwarding strategy. In our proposed model, we further consider that the trajectory of a vehicle is influenced by different social characteristics. As shown in Fig. 4, each vehicle node is influenced by its multiple social features so that the vehicles may travel to multiple specific areas. In the original PRIF data-forwarding strategy, the node encounter model is as follows:

$$E\_I_{(i,j)}(N) = \frac{Dt_{(i,j)}(N)}{It(N-1, N)} \tag{1}$$

where $E\_I_{(i,j)}(N)$ is the social strength of the node i and the node j at N time, $Dt_{(i,j)}(N)$ is the contact time between the node i and the node j, and $It(N-1, N)$ is the time interval between the $N-1$th contact and the Nth contact. Furthermore, considering that each vehicle node is influenced by its multiple social features, we improve the encounter model of the original PRIF strategy to the multi-feature-based encounter model, whose equation is described as follows:

$$E\_I_{(i,j)}(N) = \frac{Dt_{(i,j)}(N)}{It(N-1, N)} \times e^{\log \frac{\mathrm{Length}(F_i \cap F_j)}{\mathrm{Length}(F_i \cup F_j)}} \tag{2}$$

where $\mathrm{Length}(F_i \cap F_j)$ denotes the number of social features intersected by the node i and the node j, and $\mathrm{Length}(F_i \cup F_j)$ denotes the number of social features merged between the node i and the node j.

[1] In our scheme, the structure of forwarded data is divided into data header and data field, where data header includes source node name, destination node name, identifier, data size, forwarding path, current forwarding node, data creation time, data arrival time, response data flag, response data size, initial time TTL, and so on.

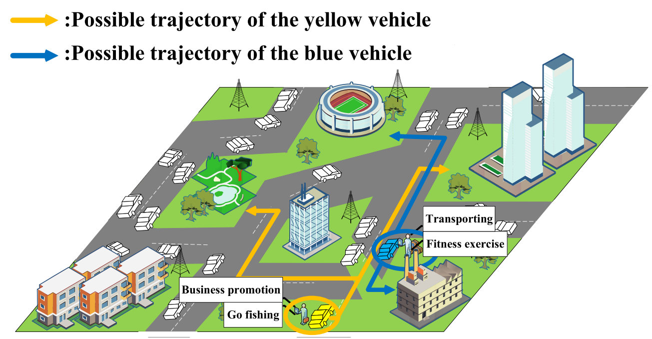

Fig. 4. Multi-feature-based SIoVs model.

B. Two-Dimensional Behavior Marker Model

In the section, we propose a 2-D behavior marker model to evaluate the forwarding capability, selfishness, and malicious tendency of vehicle nodes. In SIoVs, when the relay vehicle selected by a source vehicle is a malicious node, the malicious node may discard the data traded through money so as to obtain more money and protect its own resources as much as possible. The malicious behaviors may cause that the data cannot be forwarded to the destination node during the period time TTL and may lead to the imbalance of the data-forwarding revenue mechanism. Also, we need to consider normal loss of data packets where the data packets are not forwarded to the destination nodes. So, we construct a 2-D behavior marker model to protect the revenue mechanism, which is divided into the fog-based high-level behavior marker and the node-based low-level behavior marker.

1) Fog-Based High-Level Behavior Marker: In the section, we construct a fog-based high-level 2-D behavior marker, where we use the fog servers to calculate the 2-D marker of the vehicle nodes. In our model, we employ the entity RSU as the fog node to collect the related vehicular information, such as vehicular forwarded data identification table ST and vehicular received data identification table RT. The entity RSU collects the related information to upload to the fog server and then multiple fog servers interact with each other to calculate the high-level 2-D behavior marker Re_C of each vehicle node. Each RSU regularly collects the related vehicular information in its managing coverage area, and the fog server regularly updates the high-level 2-D behavior markers of all vehicle nodes and distributes them to the RSUs, finally the RSUs return the behavior markers to the corresponding vehicle nodes. So, each vehicle node has its high-level 2-D behavior marker $Re\_C = (Is, Rv)$, which represents its behavior attribute. Is is the high-level data-forwarding preference ratio of the vehicle node, which measures the data-forwarding preference ratio whether a node forwarding the related data is the source node or the relay node. The calculation equation of Is is defined as follows:

$$Is(i) = \frac{\sum_{x=r_{k,i},k=1}^{k=n} \alpha(x)}{\text{Length}\left(r_{1,i} \cup r_{2,i} \cup \cdots \cup r_{n,i}\right)} \tag{3}$$

where $Is(i)$ is the data-forwarding preference ratio of node i and $r_{k,i}$ is the data identification sequence received by node k to node i with $k \in \{1, 2, \cdots, n\}$

$$\alpha(x) = \begin{cases} 1, & \text{if } x's \text{ source node is } i \\ 0, & \text{otherwise} \end{cases}$$

denotes that if the source node of the data identification x is the node i itself, then $\alpha(x) = 1$, otherwise $\alpha(x) = 0$; $\text{Length}(r_{1,i} \cup r_{2,i} \cup \cdots \cup r_{n,i})$ denotes the true nonredundant number of forwarding data by node i in the related vehicular information collected by the RSU. Then Rv is the high-level real data forwarding ratio of the vehicle node, which indicates the ratio of the amount of data received by the vehicle node and the amount of data successfully forwarded to other vehicle nodes. The calculation equation of Rv is defined as follows:

$$Rv(i) = \frac{\text{Length}\left(r_{1,i} \cup r_{2,i} \cup \cdots \cup r_{n,i}\right) - \sum_{x=r_{k,i},k=1}^{k=n} \alpha(x)}{\text{Length}\left(s_{1,i} \cup s_{2,i} \cup \cdots \cup s_{n,i}\right)} \tag{4}$$

where $Rv(i)$ denotes the true data-forwarding ratio of node i, and $\text{Length}(s_{1,i} \cup s_{2,i} \cup \cdots \cup s_{n,i})$ denotes the true nonredundant number of data received by node i. Based on the collected vehicular information by the RSUs (fog nodes), the high-level 2-D behavior markers are calculated by the fog server. The evaluation accuracy of this approach depends on the number of collected vehicle nodes. There are more collected vehicular information, the evaluation of vehicle nodes by the 2-D marker is more accurate; on the contrary, the evaluation error of vehicle nodes is too high. Considering this situation, we propose the 2-D marker updating mechanism and further construct the node-based low-level 2-D behavior marker to solve the problem that since the collected vehicular information is very little, the evaluation of vehicle nodes is not accurate.

2) Node-Based Low-Level 2-D Behavior Marker: In the section, we construct a node-based low-level 2-D behavior marker. When a vehicle node does not enter into the RSU management area, it cannot upload its own information and obtain the high-level 2-D behavior marker calculated by the fog server. Therefore, we design the node-based low-level 2-D behavior marker, which is calculated by the vehicle node by using its own ST and RT. $Re\_C_i^* = (Is^*, Rv^*)$ represents the node-based low-level 2-D behavior marker of node i. Is^* denotes the data-forwarding preference ratio of the node being as a source node. However, because the node only refers to its own information, the calculated data-forwarding preference ratio is uncertain. The calculation equation of Is^* is defined as follows:

$$Is^*(i) = \frac{\sum_{y \in \text{ST}_i} \sum_{p \in y} \alpha(p)}{\text{Length}\left(s_{i,1} \cup s_{i,2} \cup \cdots \cup s_{i,n}\right)} \tag{5}$$

where $Is^*(i)$ is the low-level data-forwarding preference ratio of node i; $\text{Length}(s_{i,1} \cup s_{i,2} \cup \cdots \cup s_{i,n})$ denotes the true nonredundant number of forwarding data by node i; $Rv^*(i)$ represents the low-level data-forwarding real ratio of node i, which is also based on its own information. The calculation equation of Rv^* is defined as follows:

$$Rv^*(i) = \frac{\text{Length}\left(s_{i,1} \cup s_{i,2} \cup \cdots \cup s_{i,n}\right) - \sum_{x \in s_{i,1} \cup s_{i,2} \cup \ldots \cup s_{i,n}} \alpha(x)}{\text{Length}\left(r_{i,1} \cup r_{i,2} \cup \cdots \cup r_{i,n}\right)} \tag{6}$$

where $Rv^*(i)$ denotes the true low-level data-forwarding ratio of node i, and Length$(r_{i,1} \cup r_{i,2} \cup \cdots \cup r_{i,n})$ denotes the true nonredundant number of data received by node i.

The node-based low-level 2-D behavior marker is calculated by the vehicle node according to its own ST and RT, whose accuracy depends on the node itself. Therefore, when a node is malicious, the information of the node is not accurate, which results in the calculated low-level 2-D marker may be inaccurate. Then we need to combine the fog-based high-level 2-D behavior marker and the node-based 2-D behavior marker to construct an updating mechanism.

3) Two-Dimensional Behavior Marker Updating Mechanism: In the section, we propose a 2-D behavior marker updating mechanism to update and switch the above 2-D behavior markers, so as to solve their own shortcomings.

1) Updating high-level 2-D behavior marker
   When a vehicle node enters into the RSU management area, it first needs to upload its own ST and RT to the related fog server by the corresponding RSU. When the number of vehicle nodes that upload their information to the fog server exceeds the preset threshold ξ, the fog server exchanges its data information with other fog servers and then calculates the high-level 2-D behavior marker $Re_C = (Is, Rv)$s of these vehicle nodes by (3) and (4). Finally, the fog server updates the calculated high-level 2-D behavior markers of these vehicle nodes to all RSUs, and then the RSUs return these behavior markers to the corresponding vehicle nodes. The vehicle nodes obtain the high-level 2-D behavior marker according to the following two situations.
   a) If a vehicle node does not have its high-level 2-D behavior marker and its current managing RSU stores its high-level 2-D behavior marker, then the vehicle node directly requests to obtain its high-level 2-D behavior marker. Additionally, the node resets its ST and RT.
   b) If a vehicle node has its high-level 2-D behavior marker and it is in the RSU management area, then the vehicle node requests to obtain its own high-level 2-D behavior marker every interval time τ. Additionally, the node resets its ST and RT.
2) Updating low-level 2-D behavior marker
   When a vehicle node forwarded the related data, the vehicle node uses (5) and (6) to calculate its low-level 2-D behavior marker $Re\_C^* = (Is^*, Rv^*)$. If the vehicle node does not obtain the high-level 2-D behavior marker, then the vehicle node adopts the low-level 2-D behavior marker in the data-forwarding and incentive strategy; if the vehicle node has the high-level 2-D behavior marker and the low-level 2-D behavior marker, the vehicle node adopts the high-level 2-D behavior marker. If the vehicle node has the high-level 2-D behavior marker and the low-level 2-D behavior marker, and the updating interval time of the high-level 2-D behavior marker is more than τ, then the vehicle node adopts the low-level 2-D behavior marker. The calculation and updating procedure of the above two 2-D behavior markers is described as Algorithm 1.

The change of 2-D behavior marker can be used to distinguish the social attributes and forwarding characteristics of vehicle nodes. When Is or Is^* of a vehicle node is too big, this current node is more considered as the source node, whose ability to store the data forwarded from other vehicle nodes is limited. Therefore, it is necessary for the node to reduce the cost of receiving the data from other nodes. When Rv or Rv^* of a vehicle node is too small, this current node is considered to be selfish or malicious, whose ability to forward and receive data is false. So, the income of the type of vehicle nodes must be reduced. Additionally, in our scheme, we assume that all these vehicle nodes are not in the no-RSU managing area for a long time. Therefore, we construct the currency credit-based incentive strategy to reduce node reward to punish selfish or malicious nodes.

Algorithm 1 Two-Dimensional Behavior Marker Updating

Input: ST_i, RT_i;
Initialize number N of vehicle nodes and $Re\_C^* = (0, 1)$;
for Vehicle node i is in the RSU managing area with $i \in N$ **do**
  Node i uploads its ST_i and RT_i to the fog server by the RSU; multiple fog servers share their collected ST_i and RT_i;
  One of the fog servers calculates Re_C_i according to Equations (3) and (4), and sends Re_C_i to all other fog servers; each fog server updates Re_C_i to its managing RSUs.
end for
for Vehicle node i is in the RSU managing area with $i \in N$ **do**
  if Node i has no Re_C_i **then**
    Node i requests to obtain Re_C_i from the RSU, and uses it to participate in data forwarding; also, node i resets ST_i and RT_i;
  else if Node i has Re_C_i **then**
    Node i requests to obtain Re_C_i from the RSU every interval time τ; also, node i resets ST_i and RT_i.
  end if
end for
for Vehicle node i is not in the RSU managing area with $i \in N$ **do**
  if Node i has no Re_C_i or node i have Re_C_i whose updating interval time $>\tau$ **then**
    Node i uses $Re\_C_i^*$ to participate in data forwarding, and updates $Re\_C_i^*$ according to Equations (5) and (6) when the forwarded data is completed with the encounter node;
  else if Node i has Re_C_i whose updating interval time $<\tau$ **then**
    Node i uses Re_C_i to participate in data forwarding;
  end if
end for

C. Currency Credit-Based Data-Forwarding Incentive Strategy Based on 2-D Behavior Marker

According to the credit-based incentive strategy [28], we propose a currency credit-based data-forwarding incentive strategy based on the 2-D behavior marker. In our strategy, the data-forwarding procedure can be defined as a transaction process, where the transaction parties not only need to know each other's offer, but also need to inform their own income status and 2-D behavior marker so as to evaluate their data-forwarding preference and malicious tendency.

1) Data-Forwarding Reward: In the section, we define the data-forwarding reward model of a vehicle node. In our model, we set the buffer size of a vehicle node as its initial data-forwarding income, where each vehicle node initially has a fixed income C_0. Furthermore, two parties in a data-forwarding transaction are defined as a forwarding node and a receiving node. When the forwarding node needs to forward its data, it needs to provide its offer to the receiving node. A forwarding node evaluates and provides the data-forwarding price F according to its buffer size, the time TTL of the data, and the income status. The calculation equation of F is defined as follows:

$$F = L \times \left[\omega \times \left(1 - \frac{B(t)}{B}\right) + \upsilon \times \left(1 - \frac{\mathrm{ttl}}{\mathrm{TTL}}\right)\right] \times W_f \quad (7)$$

where L denotes the size of the forwarded data, $B(t)$ denotes the buffer size at the current time t, B denotes the initial buffer size, ttl denotes the remaining time to live of data, TTL denotes the initial time to live of data, and ω and υ are preset weight factors with $\omega + \upsilon = 1$; additionally,

$$W_f = \begin{cases} \dfrac{C \times R\upsilon(f)}{C_{\min}}, & C < C_{\min} \\ R_\upsilon(f), & \text{otherwise} \\ \dfrac{C \times R\upsilon(f)}{C_{\max}}, & C > C_{\max} \end{cases}$$

denotes the income status of the forwarding node, where the node is in a low-income status if the current income C is less than a preset $C_{\min}$, the node is in a high-income status if C is greater than a preset $C_{\max}$, otherwise the node is in a stable-income status, and $R\upsilon(f)$ is initialized to 1. When a vehicle node shows its malicious behavior, the value $R\upsilon(f)$ decreases, which indicates that the income of the node is false. When the forwarded data remains in a forwarding node, the forwarding price increases with time. After the data is forwarded, the forwarding node can release its corresponding buffer and obtain the new forwarding data and income from other nodes. The receiving node is with the ability of buffering data and assisting in forwarding nodes. Similar to the forwarding node, the receiving node needs to evaluate and provide the data-receiving price R according to its buffer size, the time TTL of the data, and the income status. The calculation equation of R is defined as follows:

$$R = L \times \left[\lambda \times \left(1-\frac{B(t) - L}{B}\right) + \eta \times \left(1-\frac{\mathrm{ttl}}{\mathrm{TTL}}\right)\right] \times \frac{1}{W_r} \quad (8)$$

where λ and η are preset weight factors with $\lambda + \eta = 1$; W_r denotes the income status of the receiving node, which is calculated as W_f. When the income of the receiving node is low, the receiving node may increase the corresponding offer to improve its income.

2) Incentive Rules: In the section, we define the incentive rules of data-forwarding transaction between vehicle nodes. When two vehicle nodes enter into each other's communication range, the forwarding node fn and the receiving node rn make their data-forwarding transaction, where F represents the data-forwarding price (offer) provided by the forwarding node fn, R represents the data-receiving price provided by the receiving node rn, W_f denotes the income status of the forwarding node fn, and W_r denotes the income status of the receiving node rn. In our incentive strategy, the detailed transaction rules are defined as follows.

1) The forwarding node fn and the receiving node rn need to inform their 2-D behavior markers, income status, and social strength related to the data destination node with each other.
2) Because the receiving node rn cannot guarantee that the data can be forwarded to the destination node, the related price needs to be adjusted according to its social strength related to the data destination node. Therefore, we adjust the forwarding price F to F^* according to (9). If $F^* \geq R$, then the current data transaction is successful and the next data-forwarding transaction continues to be judged
$$F^* = F \times \theta \quad (9)$$
where F denotes the current price (bid) of the forwarding node
$$\theta = \begin{cases} \dfrac{E\_I_{(r,d)}(N)}{E\_I_{(f,d)}(N)}, & \text{if } 0 < \dfrac{E\_I_{(r,d)}(N)}{E\_I_{(f,d)}(N)} < 1 \\ 1, & \text{otherwise} \end{cases}$$
denotes the social strength ratio of the two transaction parties related to the data destination node.
3) When $F^* < R$, the two transaction parties enter into the second bargaining phase.
4) When $W_r > R\upsilon(r)$, F^* remains unchanged. Considering that the income status of the receiving node is good, we adjust R according to the following equation:
$$R^* = R \times (1 - Is(r)) \quad (10)$$
where R^* denotes the second price (bid) of the receiving node and $Is(r)$ is the data forwarding preference ratio of the receiving node rn.
5) When $W_r < R\upsilon(r)$ and $W_f > R\upsilon(f)$, R remains unchanged. Considering that the income status of the forwarding node is good, we further adjust F^* according to the following equation:
$$F^{**} = F^* \times W_f \quad (11)$$
where W_f denotes the income status of the forwarding node fn.
6) When $W_r < R\upsilon(r)$ and $W_f < R\upsilon(f)$, R remains unchanged. We adjust R and F^* according to (10) and (11), respectively.
7) If the condition $F^* \geq R^*$ & $F^{**} \geq R$ & $F^{**} \geq R^*$ holds after the second negotiation, then the current data transaction is successful and the next data transaction

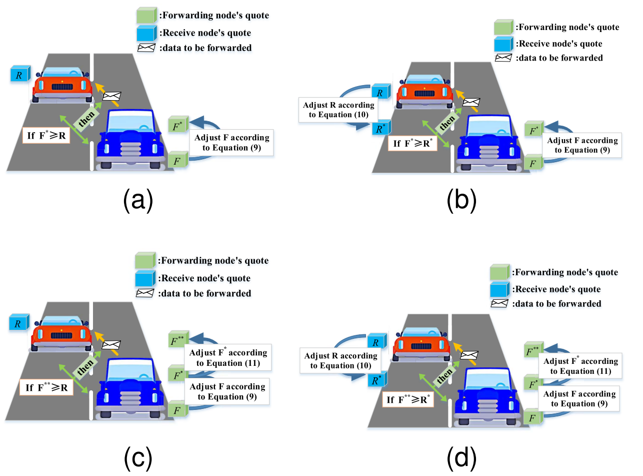

Fig. 5. Different cases of successful data-forwarding transaction. (a) Case $F^* \geq R$. (b) Case $F^* \geq R^*$. (c) Case $F^{**} \geq R$. (d) Case $F^{**} \geq R^*$.

is started; otherwise, the current data transaction is canceled and the next data transaction begins. As shown in Fig. 5, according to different conditions, there are four successful data forwarding cases. Fig. 5(a) shows the success of the first bargaining and the completion of data forwarding. Fig. 5(b)–(d) shows the success of the second bargaining and the completion of data forwarding. The detailed transaction rules in our incentive strategy are described as Algorithm 2.

3) Incentive Income Analysis: In the section, we analyze the effect of vehicle behaviors on income to show that our 2-D behavior-marker-based data-forwarding incentive scheme can motivate vehicle nodes to cooperate with each other. In the following, we analyze the behaviors of forwarding node fn and receiving node rn.

1) Additional expenditure for not forwarding data
The data M occupies the node buffer and its time TTL gradually decreases if the forwarding node fn does not forward M. According to the following equation, we can calculate the additional expenditure c_notF that the forwarding node does not forward data at least:

$$c\_notF = \min\left\{L_M \times \omega \times W_r \times \frac{L_M}{B},\ L_M \times \upsilon \times W_r \times \frac{\mathrm{ttl}^t - \mathrm{ttl}^{t+1}}{\mathrm{TTL}}\right\} \quad (12)$$

where L_M denotes the size of M; ttl^t and $\mathrm{ttl}^t + 1$ denote the remaining times to live of M at t and $t + 1$ times, respectively; the other symbols are the same as that of (7).

2) Additional expenditure for forwarding data
When the forwarding node fn successfully forward the data M, it may incur additional expenditure due to the second negotiation of our proposed transaction rules. According to the following equation, we calculate the minimal additional expenditure c_F that the forwarding node forward its data:

$$c\_F = \min\left\{R^* - F^*, R - F^{**}, R^* - F^{**}\right\}. \quad (13)$$

Algorithm 2 Currency Credit-Based Incentive Strategy Based on 2-D Behavior Marker

Input: $M \in$ *Dataset to be forwarded*, Re_C_f *or* $Re\_C_f^*$; Re_C_r *or* $Re\_C_r^*$, F, R;
Output: Data forwarding result (i.e. whether the data M is forwarded to the node rn)

```
Considering that the receiving node rn may not necessarily forward the data M to the destination node, the forwarding node fn adjusts F to F* according to Equation (9).
for M ∈ Dataset to be forwarded do
    if F* ≥ R then
        the transaction of M is completed and the next data transaction begins;
    else
        the second price negotiation stage begins as follows:
        if W_r > Rv(r) then
            R* is calculated according to Equation (10);
        else if W_r < Rv(r) and W_f > Rv(f) then
            F** is calculated according to Equation (11);
        else if W_r < Rv(r) and W_f < Rv(f) then
            R* is calculated according to Equation (10) and F** is calculated according to Equation (11).
        end if
        if F* ≥ R* & F** ≥ R & F** ≥ R* then
            the transaction of M is completed and the next data transaction begins;
        end if
    end if
end for
```

Obviously, we can get that $c\_notF > 0 > c\_F$, thus the forwarding nodes can actively participate in data forwarding.

3) Additional expenditure for not receiving data
If the receiving node rn does not receive the data M, its buffer is idle. So, this status can reduce the next price provided by the receiving node rn itself. According to the following equation, we calculate the minimal additional expenditure c_notR that the receiving node rn does not receive the data:

$$c\_notR = L_M \times \lambda \times \frac{L}{B} \times \frac{1}{W_r} \quad (14)$$

where the symbols are the same as that of (8).

4) Additional expenditure for receiving data
When the receiving node rn receives the data M, its buffer size becomes smaller, and it gains the corresponding income R. According to the following equation, we calculate the minimal additional expenditure c_R that the receiving node rn receives the data:

$$c\_R = -\left(R + L_M \times \lambda \times \frac{L}{B} \times \frac{1}{W_r}\right) \quad (15)$$

where the symbols are the same as that of (8). Therefore, we can get that $c\_notR > 0 > c\_R$. Because the additional expenditure for receiving data is less than that of non-receiving data, the receiving node rn is willing to receive the data.

IV. Experimental Simulation and Analysis

In the section, we make experiments to evaluate and analyze the performance of our proposed scheme. In the experiments, we mainly evaluate the successful ratio of data delivery generated by our scheme under different ratios of selfish and malicious nodes, different TTLs, and different buffer sizes. The evaluation parameters are described as follows.

1) *Delivery Ratio:* It is the ratio of the number of data that can successfully reach the destination nodes to the total number of data sent by the source nodes within a given simulation time (excluding the duplicated data).
2) *Selfish Nodes Ratio:* It is the ratio of the number of selfish nodes to the number of all vehicle nodes in the simulation experiments.
3) *Malicious Nodes Ratio:* It is the ratio of the number of malicious nodes to the number of all vehicle nodes in the simulation experiments.

Furthermore, based on the above evaluation parameters, we compare our scheme with the NISOVCM scheme [28] and the PRIF scheme [29].

A. Experimental Setting

In this section, we show the experimental environment and setting used to evaluate the performance of our scheme. In the experiments, we use the opportunistic network environment (ONE) simulator [30] to test our scheme, where the ONE simulator can generate various reports about node movement and data transfer. We use the points-of-interest (POI) movement model in our experiments, which is used to describe the moving model that the vehicle nodes depend on their interests. Since the POI model contains multiple POI regions, which indicate the regions to which the points of interest are related, we may set the movement of vehicle nodes according to the preset probabilities. Additionally, in the experiments we set that: 1) the group of selfish nodes can participate in forwarding the data of these selfish nodes and 2) the group of malicious nodes cannot participate in any data forwarding, but these malicious nodes participate in receiving data.

In our experiments, we set eight groups of experimental nodes, including four groups of normal vehicles, one group of selfish vehicles, one group of malicious vehicles, one RSU group, and one fog server group. Furthermore, the normal vehicles group contains 40 vehicle nodes without any selfish vehicles or malicious vehicles, the RSU group contains 12 nodes, and the fog server group contains four nodes, where each fog server manages three RSU nodes. Additionally, the normal vehicles group uses the shortest path map-based movement model, where the vehicle nodes are regulated to move on the road. The RSU group and the fog server group both use the stationary movement model. In the POI movement model, we compare our scheme with these NISOVCM and PRIF schemes under different ratios of selfish and malicious nodes. According to the interests of vehicle nodes, the PRIF scheme classifies the community attributes of vehicle nodes to determine whether the encountered nodes can forward data, but the scheme does not consider the selfishness of vehicle nodes. The NISOVCM scheme proposes a vehicle node incentive strategy based on the overdraft virtual currency mechanism. Compared with these two schemes, our scheme can comprehensively evaluate a vehicle node with the assistance of a forwarding table, a receiving table, and a fog server. Furthermore, based on social attributes, our scheme provides a more accurate way to determine whether the data is forwarded by calculating the data-forwarding income between vehicle nodes.

TABLE I

Parameter Setting of Experimental Environment

Description	Value
Simulation time	50000s
Time window	30s
Number of simulations	30
Area	$4500\times3400\text{m}^2$
Vehicle speed	2.7∼13.9m/s
Wait time at destination node	100∼200m/s
TTL	600min
Number of nodes in normal group	40
Number of nodes in RSU group	12
Number of nodes in fog server group	4
Event interval	50∼90s

TABLE II

Parameter Setting of Our Scheme

Description	Value
$Re\_C_i^*$	(0,1)
Re_C_i	(0,0)
τ	1300s
ω	0.6
υ	0.4
λ	0.4
η	0.6

The parameter setting of the experimental environment is described in Table I. The buffer of the mobile node is set to 20 MB and the time TTL is set to 600 min. Also, two interfaces are set for wireless transmission: 1) the first communication distance is 10 m and the transmission speed is 2 Mb/s, which are used between vehicle nodes; and 2) the second communication distance is 300 m and the transmission speed is 10 Mb/s, which are used for the interaction between mobile nodes and RSUs. The vehicle node generates a data event every 50–90 s, and the destination nodes of the data are also the vehicle nodes. The size of each data is 0.5–1 Mb, the transmission speed between RSUs and fog servers is 20 Mb/s, and the transmission speed between fog servers is 20 Mb/s. To test the performance of these schemes, we make the experiments by changing the following parameters: different buffer sizes (10–50 Mb), different TTLs (600–3600 min), different ratios of selfish nodes (10%–50%), and different ratios of malicious nodes (10%–50%). Additionally, the parameter setting of our scheme is described as Table II.

B. Simulation Results and Analysis

In the section, we first test and evaluate the effect of the low-level and high-level 2-D behavior markers on the simulation data. Furthermore, we evaluate and analyze the performance

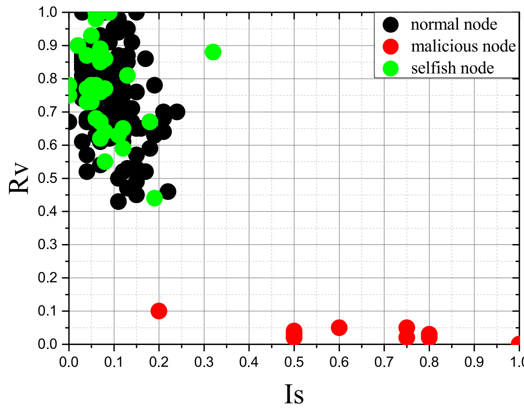

Fig. 6. Low-level 2-D behavior markers.

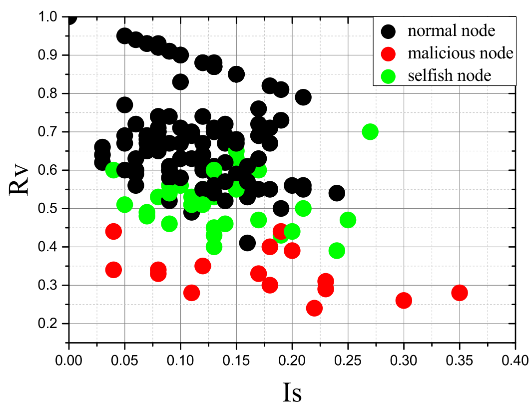

Fig. 7. High-level 2-D behavior markers.

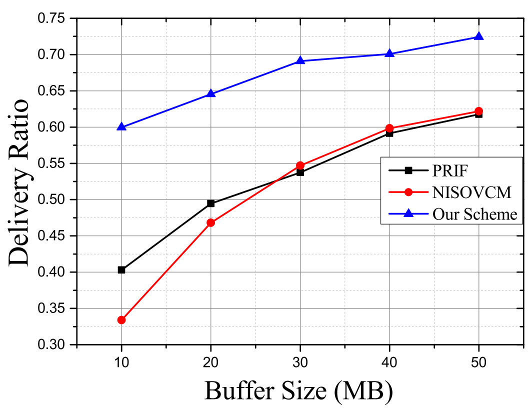

Fig. 8. Performance comparison on buffer sizes.

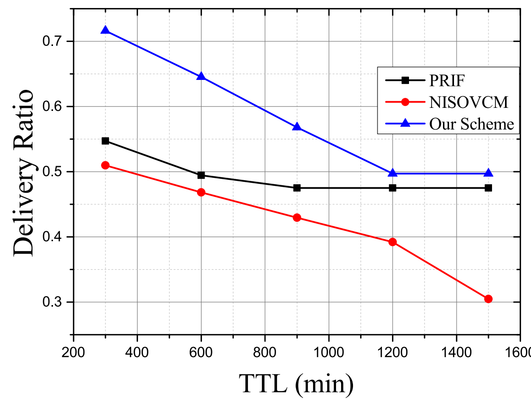

Fig. 9. Performance comparison on TTLs.

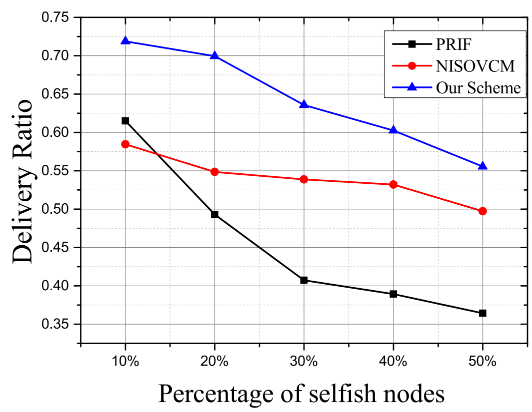

Fig. 10. Performance comparison under different ratios of selfish nodes.

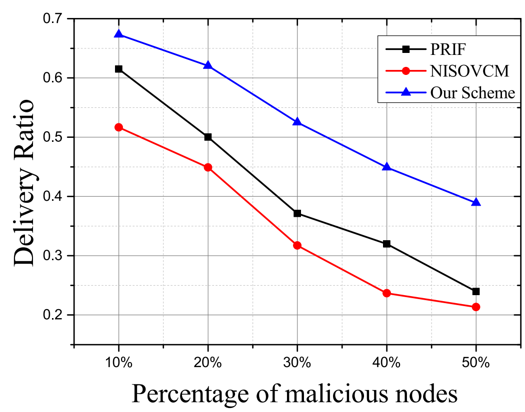

Fig. 11. Performance comparison under different ratios of malicious nodes.

of our scheme and other two schemes under different ratios of selfish and malicious nodes, different TTLs, and different buffer sizes. Each test is run 30 times to obtain the average values of these experimental results. The experimental results are shown in Figs. 6–11.

Fig. 6 shows the low-level 2-D behavior markers. In the experiment, the ratio of normal nodes is set to 70%, the ratio of selfish nodes is set to 20%, the ratio of malicious nodes is set to 10%; the time TTL is set to 600 min, and the buffer size is set to 30 MB. The low-level 2-D behavior marker $Re\_C^* = (Is^*, Rv^*)$ of each vehicle node is initially set to $(0, 1)$. It can be seen from Fig. 6 that the normal vehicle nodes are basically in the upper left of the 2-D coordinate system and the malicious vehicle nodes are located at the bottom of the 2-D coordinate system, but the selfish vehicle nodes are mixed with normal nodes in the 2-D coordinate system. For example, the 2-D behavior marker of the normal node has $Is \in (0, 0.24)$ and $Rv \in (0.45, 1)$, the 2-D behavior marker of the selfish node has $Is \in (0, 0.32)$ and $Rv \in (0.44, 1)$, and the 2-D behavior marker of the malicious node has $Is \in (0.5, 1)$ and $Rv \in (0, 0.1)$. Our proposed low-level 2-D behavior marker can distinguish normal nodes and malicious nodes, but cannot

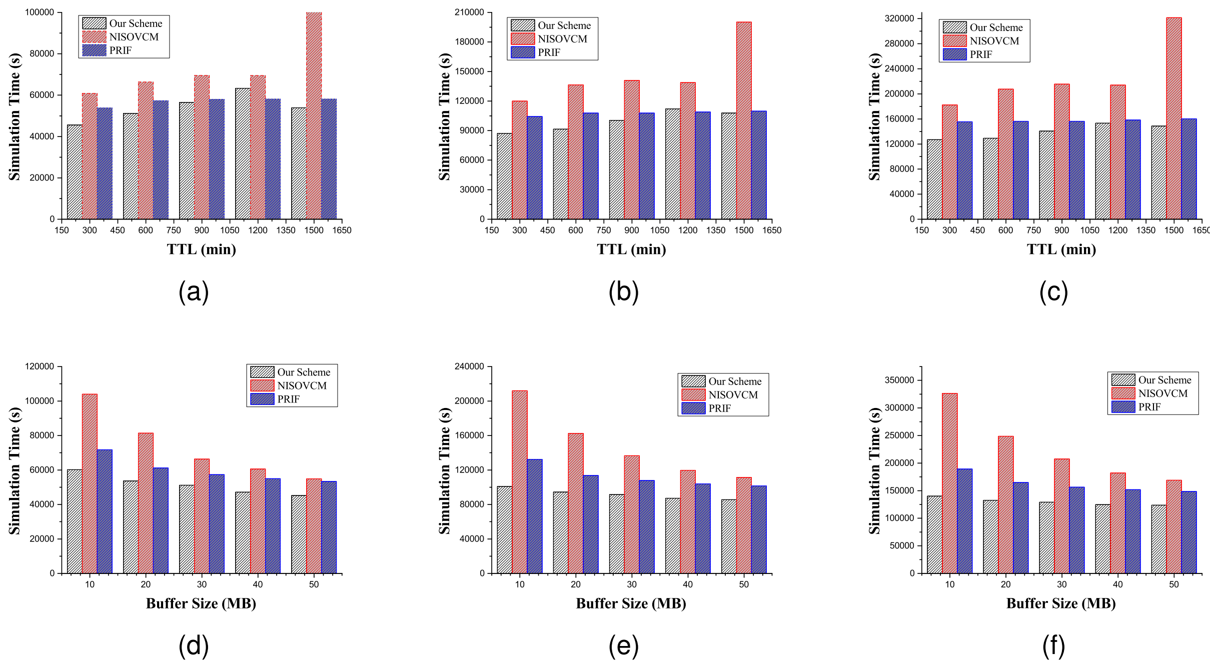

Fig. 12. Time-consuming comparison of different data-forwarding schemes. (a) Number is 500 under different TTLs. (b) Number is 1000 under different TTLs. (c) Number is 1500 under different TTLs. (d) Number is 500 under different buffer sizes. (e) Number is 1000 under different buffer sizes. (f) Number is 1500 under different buffer sizes.

distinguish selfish nodes. Therefore, it has some limitations to distinguish the behaviors of vehicle nodes.

Fig. 7 shows the high-level 2-D behavior markers. It can be seen from Fig. 7 that the normal vehicle nodes are basically in the upper left of the 2-D coordinate system, the malicious vehicle nodes are located at the bottom of the 2-D coordinate system, and the selfish vehicle nodes are in the middle of the 2-D coordinate system. Normal vehicle nodes are actively involved in data forwarding, where the 2-D behavior marker of the normal node has $Is \in (0, 0.2)$ and $Rv \in (0.5, 1)$. Selfish vehicle nodes only participate in data forwarding, where the 2-D behavior marker of the selfish node has $Is \in (0.05, 0.25)$ and $Rv \in (0.4, 0.6)$. The 2-D behavior marker of the malicious node has $Is \in (0.05, 0.35)$ and $Rv \in (0.2, 0.4)$. Therefore, our high-level 2-D behavior marker can distinguish normal vehicle nodes, selfish vehicle nodes, and malicious vehicle nodes to make accurate incentive strategies.

Fig. 8 shows the experimental results on buffer sizes. It can be seen from Fig. 8 that the successful data delivery ratio of three schemes increases with buffer size. The data delivery ratio of our proposed scheme is more stable and efficient than the other two schemes. For example, the data delivery ratio of our scheme can reach 72.44% when the buffer size is 50 MB, the data delivery ratio of the PRIF scheme is 61.77%, and the data delivery ratio of the NISOVCM scheme is 62.19%. Compared with the pure node incentive strategy, the data delivery ratio of our scheme increases 10.25%.

Fig. 9 shows the experimental results on TTLs. It can be seen from Fig. 9 that with the increase of TTL, the data delivery ratio of three schemes decreases, but the data delivery ratio of our scheme is significantly higher than those of the other two schemes. For example, the data delivery ratio of our scheme is 56.79% when the time TTL increases to 900 min, the data delivery ratio of the NISOVCM scheme is 42.94%, and the data delivery ratio of the PRIF scheme is 47.51%. Compared with the pure node incentive strategy, the data delivery ratio of our scheme is 13.85% higher than that of the NISOVCM scheme.

Fig. 10 shows the experimental results under different ratios of selfish vehicle nodes. It can be seen from Fig. 10 that with the increase of the ratio of selfish nodes, the data delivery ratio of the node incentive strategy decreases slightly, and the data delivery ratio of the data-forwarding scheme that does not consider node selfishness is greatly reduced. Obviously, the data delivery ratio of our scheme is significantly higher than those of the other two schemes. For example, when the ratio of selfish nodes reaches 50%, the data delivery ratio of our scheme is 49.72%, the data delivery ratio of the NISOVCM scheme is 47.51%, and the data delivery ratio of the PRIF scheme is 30.47%. Compared with the pure node incentive strategy, the data delivery ratio of our scheme is 2.21% higher than that of the NISOVCM scheme.

Fig. 11 shows the experimental results under different ratios of malicious vehicle nodes. It can be seen from Fig. 11 that with the increase of the ratio of malicious nodes, the data delivery ratios of the PRIF and NISOVCM schemes are gradually decreasing, but the data delivery ratio of our scheme is relatively stable. For example, when the ratio of malicious nodes increases to 50%, the data delivery ratio of our scheme is 38.92%, the data delivery ratio of the PRIF scheme is 21.33%, and the data delivery ratio of the NISOVCM scheme is 23.96%. According to the experimental results, our scheme can effectively deal with the behaviors of malicious nodes, but the NISOVCM scheme has a weak ability to deal with the behaviors of malicious nodes.

Fig. 12 shows the time-consuming comparison of three schemes when the numbers of successful forwarded data are required to 500, 1000, and 1500, respectively. In the experiment, there are three kinds of vehicle node, where the ratios of normal nodes, selfish nodes, and malicious nodes are also set to 70%, 20%, and 10%, respectively. Fig. 12(a)–(c) shows the time-consuming comparison under different TTLs. Fig. 12(d)–(f) shows the time-consuming comparison under different buffer sizes. As shown in Fig. 12, our scheme has the advantage of time-consuming, compared with the NISOVCM and PRIF schemes. For example, when the TTL is 600 min, the time consumption required by our scheme is 67.01% of the NISOVCM scheme and 84.84% of the PRIF scheme in Fig. 12(c); when the buffer size is 40 MB, the time consumption required by our scheme is 68.53% of the NISOVCM scheme and 82.16% of the PRIF scheme in Fig. 12(f). The experimental results show that our scheme is superior and more stable than the NISOVCM and PRIF schemes.

Therefore, compared with the PRIF and NISOVCM schemes, the whole experimental results show that our scheme is more efficient and stable under different ratios of selfish and malicious nodes, different TTLs, and different buffer sizes. Our scheme not only employs the vehicular social attributes to improve the data delivery ratio, but also combines the 2-D behavior marker and the currency credit-based incentive strategy to reduce the effect of malicious nodes and encourage the normal and selfish nodes to participate in data forwarding.

V. Conclusion

In SIoVs, vehicle nodes often show their personal and social selfishness in data forwarding, whose selfishness greatly influences the delivery ratio of data forwarding. In this article, we propose a 2-D behavior-marker-based data-forwarding incentive scheme to motivate vehicle nodes to participate in data forwarding in fog-computing-based SIoVs. First, we construct the fog-based high-level behavior marker and the node-based low-level behavior marker according to the locations of vehicle nodes, which are used to evaluate the selfishness and malicious tendency of vehicle nodes. Second, we combine the behavior marker and the currency credit-based incentive strategy to reduce node reward to punish selfish and malicious nodes. Furthermore, the social attributes of vehicle nodes are added to the incentive method, which are used to accurately evaluate the forwarding price of vehicle nodes. Compared with other related works, our proposed scheme can completely evaluate the behaviors of vehicle nodes and can further promote the cooperation of data forwarding. The experimental results show that our scheme is more efficient and stable in data forwarding.

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