Social acquaintance based routing in Vehicular Social Networks

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HIGHLIGHTS

- This paper presents a novel protocol based on social acquaintance for data forwarding in VSNs.
- Social feature metrics are considered for decision-making.
- Reduced End-to-End delay and improved packet delivery ratio.
- Simulations were performed to evaluate the proposed protocol under different scenarios.

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ABSTRACT

The concept of Internet of Things (IoT) provides us the opportunity to interconnect different objects with the communication and processing capabilities for a diverse range of applications. Recently, Vehicular Social Networks (VSNs) have been introduced through the combination of relevant concepts from two primary disciplines, i.e., social networks and Vehicular Ad hoc Networks (VANETs). Inspired from the social acquaintance in our daily life, we present a Social Acquaintance based Routing Protocol (SARP) for VSNs, which collectively consider three social feature metrics to make a forwarding decision. The proposed protocol aims to reduce End-to-End delay and improve packet delivery ratio in VSNs. Additionally, SARP overcomes the shortcoming of topology based routing and optimum local situation of geographically based routing protocols by considering the global and local community acquaintance of nodes. We performed extensive simulations under constant node density with different mobility speed and constant speed with varying node density to study the effect of node mobility speed and density on end-to-end delay and packet delivery ratio. The simulation results show that SARP outperforms GPSR by 22% and 26% in terms of end-to-end delay and packet delivery ratio respectively. Also, SARP outperforms AODV in terms of end-to-end delay.

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1. Introduction

Vehicular Ad hoc Network (VANET) is a unique form of Ad hoc networks, created by vehicles with restricted mobility on roads and streets with data processing and wireless communication capabilities. These vehicles either communicate directly or through Road Side Units (RSUs) utilizing different communication infrastructures, including 3G/4G, WiFi, etc. Network resources are used to access and obtain data from other networks. VANETs have the capabilities to be deployed in different operational environments for a diverse range of applications. In other words, VANETs are sparse Ad hoc networks formed by vehicles to communicate opportunistically on contact. Due to its easy to deploy nature and diverse possible range of applications in a pervasive environment, VANETs have attracted the attention of not only academicians but also from industrial leaders. Typical applications of VANETs include intelligent traffic control systems, collision warnings, active navigation systems, and passenger entertainment/comfort services.

Quite recently, the research community in the field of communication and technology has been greatly attracted by Social Network Analysis (SNA) and its applications to design new algorithms and protocols for socially aware networking, such as Mobile Social Networks (MSNs), Vehicular Social Networks (VSNs), and Internet of Things (IoT). The motivation behind the inheritance of social networks in communication networks is that all entities have interdependencies which relate them to each other in one
way or another. These interdependencies include physical contact, mutual interest, similarity, group participation, and much more. SNA not only helps us to define these interdependencies but can also be exploited to correlate them. Social networking is the grouping of entities based on their social interdependencies to improve the effectiveness and efficiency of network services [1,2]. Some algorithms and protocols have been proposed so far, based on the social interaction of entities (nodes, devices, people, and systems), which has shown that social interactions of nodes can be exploited to achieve high efficiency and effectiveness within mobile communication systems [3].

The inheritance of social networks has a lot of potentials which can be exploited in a vehicular environment. Vehicular mobility and density are two of the main factors that significantly influence the communication in the vehicular environment. Mobility directions and speed limitations on public roads restrict vehicular mobility. However, vehicular density is affected by the number of vehicles moving on a specific route within a particular period of the day/week. During rush hour, traffic jams result in higher vehicular density. Density variations during different times of day/week characterize vehicular dynamic network topology, making data sharing and communication a challenging task in the vehicular environment. Besides, vehicular mobility depends on drivers’ interests, behaviors, and routine. For example, on weekdays, the commuters often repeat the same path at the same time and to the same destinations, such as work offices, universities, schools, etc. Similarly, different destinations, including parks, cinemas, shopping malls, etc., are the most visited destinations for commuters on weekends. These vehicles are controlled by humans exhibiting some social behaviors. However, unlike Mobile Social Networks (MSNs), vehicular mobility is restricted to roads and streets. These vehicles communicate on opportunistic encounter within each other’s communication range.

In a vehicular environment, commuters encounter other vehicles/passengers on their trajectories with a similar profile moving on the same street and facing the same traffic conditions. These commuters can share valuable information along the roads and may include traffic information, personal information, and vehicle information. Socially-aware techniques are applied to exploit the social similarity of nodes to improve data delivery services and connectivity in a vehicular environment. Inheritance of social networks into vehicular networks has been identified as one of the most efficient solutions for a diverse range of applications. These applications can be mainly divided into four categories; (a) Safety-based applications, (b) Convenience-based Applications, (c) Comfort-based applications, and (d) Entertainment-based applications.

After homes and offices, regular citizens spend considerable time in vehicles based on their daily schedules. Different from MSNs, where human beings interact with each other using their smart devices, network entities in VSNs are heterogeneous including OBUs, RSUs, as well as drivers’ and passengers’ smart devices. As shown in Fig. 1, VSNs incorporate relevant features and concepts from two different fields namely VANETS and social networks. VANETs provide the underlying communication network infrastructure, whereas social networks contribute to the social knowledge of entities. VSNs can be deployed in different scenarios such as urban and highway, where it can be either centralized or distributed in nature. Based on the underlying communication architecture, three types of communication relations are found in VSNs: human-to-human, humans and machines, and machines-to-machines. Similarly, unique characteristics of VSNs and particular applications environment distinguish VSNs from traditional MSNs and VANETs.

Recently, many efforts have been made to propose different algorithms and architectures that incorporate the concepts of social networks to support a variety of mobile social applications [4–7]. However, these solutions have mainly focused on Delay Tolerant Networks (DTNs) and MSNs. Quite recently, a few works addressed the incorporation of social networks in vehicular networks [8–16]. It has been demonstrated that the incorporation of social networks into vehicular networks positively influence the services and communication. However, some technical challenges arise that need to be addressed. Dynamic network topology and high vehicular mobility make application development in VSNs a challenging task. Similarly, opportunistic and short-term communication contacts in VSNs demand for efforts to develop new algorithms to accommodate different applications. Data dissemination, routing, mobility modeling, simulation, privacy, and security are other issues which need to be considered.

Social relationships are relatively stronger and stable as compared to communication links between mobile nodes, which can be exploited to enhance data transmission [17]. However, some questions arise considering the vehicular environment. Does it has social properties? Is there any permanence of social behaviors in vehicular mobility? How effective is to examine social behavior in the vehicular environment? Some works exist in literature to answer these questions [18–20]. Authors in [19] analyzed real data sets and found that vehicular mobility shows small world phenomenon. Similarly, the study also indicates the existence of communities with similar interests. Social ties and social community are widely used concepts to enhance data dissemination in socially-aware networks. Community members are expected to communicate more frequently as compared to other nodes out of the same community. However, for inter-community communication, global knowledge of popularity of nodes is required. Similarly, for intra-community data dissemination and forwarding, social ties can be exploited to enhance data delivery.

Improving QoS in VSNs is one of the challenging tasks due to higher mobility and dynamic network topology. Information sharing and prediction based algorithms in VSNs is vulnerable to packet drop and privacy attacks. Similarly, resources utilization and traffic congestion are also the key factors to consider while developing algorithms/protocols for VSNs. In short, to overcome these challenges efforts are needed with appropriate mechanism to deal with highly dynamic nature of VSNs and intermittent connectivity to enhance data delivery.

In this paper, we consider social characteristics of nodes in the vehicular environment and propose a novel protocol for data dissemination in VSNs named as SARP (Social-Acquaintance based Routing Protocol). This protocol exploits the social metrics in a fully distributed manner using characteristics of Ad hoc and delay tolerant networks. This work differs from existing works as follows. First, community acquaintance is defined to quantify the global and local importance of intermediate nodes. Second, community acquaintance is jointly considered with node centrality and activeness with minimum possible overhead to select the next relay node. Third, we propose a new protocol (SARP) to enhance data delivery in VSNs with minimized end-to-end delay and improved packet delivery ratio. Finally, extensive simulations are performed to evaluate the performance of proposed protocol in VSNs.

The rest of the paper is organized as follows. Related work on socially-aware routing and dissemination protocols are presented in Section 2 with motivation for our proposed model. In Section 3, we provide an overview of proposed protocol and social features which are considered to develop the forwarding decision. Section 4 describes the simulation setup. Before concluding remarks in Section 6 with future work, simulation results are presented in Section 5.
2. Related works and motivation

Data dissemination in VSNs is one of the main challenges due to highly dynamic nature and intermittent connectivity in the vehicular environment. Unlike wireless sensor networks, where sensor nodes directly transmit sensed data to the base station [21], in VSNs, an end-to-end path does not exist, and data is forwarded in store-carry-and-forward fashion. Different features and parameters may be considered to enhance data dissemination in VSNs. In [22] authors have profoundly studied different data dissemination approaches in VSNs. In the study, it is shown that social behaviors and mobility pattern of nodes\(^1\) are being exploited to design content dissemination protocols. Similarly, inextricable properties of mobile devices and their users (i.e., their mobility patterns, interdependent social behaviors) are being utilized in other communication networks, such as Pocket Switched Networks (PSNs) [23], Delay Tolerant Networks (DTNs) [24], Socially Aware networking (SAN) [25], and Opportunistic Networks (OppNets) [26].

SAN provides a ground to inherit social properties of nodes into the vehicular environment, where a group of individuals having common interests may share information along the roads. Socially based protocols help to identify socially-similar nodes based on common interest, community affiliation, similar route, and destination. Stability of social ties and less frequent variation in social relationships are the key initiatives to inherit social properties in the vehicular environment to enhance data dissemination. Recently, nodes’ social properties are extensively analyzed and considered by the research community to design new routing protocols for socially-aware networks [25,27–29].

Quite recently, Xia et al. in [25] have presented a novel interest-based forwarding scheme for socially aware networks. The proposed protocol, BEEINFO (Artificial BEE Colony inspired INterest-based Forwarding), exploits food foraging behavior of bees to record information of different communities passing through. Bees’ awareness capability has been introduced in VSNs considering three distinct areas, i.e., shopping mall, hospital, and school. Vehicles along their routes collect community information and estimate community density. Community density is defined as the number of nodes in a particular community. Individuals with similar and shared interests build communities, and it is understood that members of the same community meet more often than members out of the community. LABEL [30] is one of the well-known routing protocols based on community concepts to deliver messages only to the member nodes of destination community. Similarly, following the same idea, BUBBLE RAP [31] enhance routing performance considering central nodes with community detection, resulting in high cost for maintenance and construction of socio-aware overlay.

To reduce end-to-end delay and achieve higher delivery ratio is a challenging goal to be achieved in VSNs. Gu et al. in [32] proposed a socially-aware routing protocol with fuzzy logic to achieve this aim. This fuzzy logic algorithm not only depends on traditional greedy approach but also exploits the social behaviors of nodes, i.e., centrality. Cunha et al. in [33] considered the daily variation of traffic flow and social ties among vehicles to propose a data dissemination protocols in vehicular networks. The social metrics considered by authors include clustering coefficient and node degree to select the best node for data dissemination in the vehicular environment. Besides, some other works in the literature [34–39] combine community awareness with other social metrics, i.e., similarity, node centrality, and betweenness to enhance inter-community and intra-community data delivery. These protocols consider historical encounter of nodes to predict the contact probability for data forwarding.

Apart from social network analysis, based on underlying communication architecture of VSNs, the traditional performance metrics including delivery ratio, bandwidth usage, and data delivery delay affect the QoS of VSNs. However, some applications, i.e., traffic, safety, and emergency information dissemination require short data delivery delay. On the other side, some applications demand higher data delivery as compared to reduced end to end delay such as entertainment applications. However, exploring the efficient modeling of socially aware metrics in VSNs is a challenging task. Efforts are still needed to exploit application-oriented social metrics to design data dissemination protocols for VSNs.

3. Overview of SARP

Reliable and efficient data dissemination in the vehicular environment is one of the most extensively studied issues in literature. Higher mobility and dynamic network topology are the key factors making data dissemination in the vehicular environment as one of the challenging tasks and have attracted the research community. Traditional routing protocols for VANETs, MANETs, and other large-scale networks often use the geographical information or network topology information for making a routing decision [40,41]. Routing protocols based on network topology cannot be applied to VSNs due to its dynamic network topology.
Similarly, routing protocols based on geographical information can be helpful in highway scenarios but might end up in local optimum in urban areas. On the other hand, the social relationships among nodes in the vehicular environment are relatively stronger and stable as compared to node mobility. In this paper, we propose a multi-dimensional routing protocol, which exploits the nodes’ social characteristics such as community acquaintance, node centrality, and activeness to route a message from a source to destination in VSNs. Nodes belong to different communities based on their interest and geographical location. Compared to existing social-aware routing protocols, SARP not only considers the current values of parameters but also examines the historical values for decision making which makes it more flexible and reliable. Similarly, global importance of relay nodes is considered to overcome the local optimum problem of geographically based routing protocols.

We consider an application scenario for information sharing and develop a mechanism to calculate a priority value of next relay node. The message is forwarded in store-and-carry fashion from a source node to the destination node within the same or different community. People with the same interests or from the same community usually meet more often and have the greater probability to meet in future as compared to other members of communities or with different interests. We consider three research groups (Group A, Group B, and Group C) with different research direction with mutual collaboration, where the members of the same research group have greater interaction and probability to meet as compared to members of other research groups. If a member of Group A wants to deliver a file to someone in the same research group, he/she may directly hand over the desired file personally or can deliver the file to a person who has greater community acquaintance as compared to him/her. Why do we not consider node centrality to deliver the message/file as most of the previous work do? A person or node can have higher node centrality, but it may not be sufficient to deliver a message to the destination node as compared to the one who has greater interaction within the same community at the same time. Similarly, does it guaranty that a message will be delivered to the destination for sure by choosing a relay node with high community acquaintance and node centrality? To increase the probability of message delivery, we also consider node activeness. Consequently, a person who has higher community acquaintance, the high degree of centrality and most active in the community can be the most suitable relay candidate to deliver a message. Similarly, a person who is active and has more connection within Group A but no or less acquaintance with members of Group B or Group C cannot be a suitable relay for information delivery from Group A to Group B or Group C. The global community acquaintance is required to route a message from source to destination community during inter community communication.

As shown in Fig. 2, if the source node s wants to send a packet to a destination node d outside community A, it can choose one of the nodes i, j, and k as a relay node. Degree centrality for node i, j, and k is the same (i.e., 5); however, the neighbors of j remain the same while the neighbor list of node j and k include some transit nodes. This indicates that node i and k are more active as compared to node j. Besides, the interaction of node i is limited to members of community A; however, node k has an interaction with nodes from community C, which may increase the probability of message delivery towards destination community. In other words, node k has higher global community acquaintance as compared to node i and j. Following this, we consider these three social feature metrics to define priority value for data forwarding to choose next relay node. The following subsections describe how we estimate these social feature metrics.

3.1. Community acquaintance

Community acquaintance is the global and local measurement of node’s popularity in a network. Higher global community acquaintance increases the probability of inter-community packet forwarding, and higher local community acquaintance increases the probability of intra-community forwarding. In our proposed method we use the following equation to estimate nodes’ community acquaintance.

\[ CAcq_{ni} = \alpha CAcq_{localn_i} + (1 - \alpha)CAcq_{globaln_i} \]  

(1)

Where \( \alpha \) is a control variable, and the values are used in our proposed model are 1 and 0 for intra-community and inter-community packet forwarding respectively. Global community acquaintance is required for inter-community forwarding, but once a packet reaches destination community, the local community acquaintance is considered for packet forwarding. Node encounter is measured when two nodes are within the communication range of each other, and a hello message is successfully exchanged.

\[ CAcq_{localn_i} = \sum_{j=1}^{N} \text{Encounter}_{n_i,n_j} \]  

(2)

Equation 2 is used to calculate the local community acquaintance of node \( n_i \), Where \( \text{Encounter}_{n_i,n_j} = 1 \), if a hello message is successfully exchanged between \( n_i \) and \( n_j \) and \( n_i \) and \( n_j \) belong to the same community. \( N \) is the total number of nodes in the same community.

Similarly, Eq. (3) is used to calculate the global community acquaintance of node \( n_i \), Where \( \text{Encounter}_{n_i,n_j} = 1 \), if a hello message is successfully exchanged between \( n_i \) and \( n_j \) and \( n_i \) and \( n_j \) do not belong to the same community. \( M \) is the total number of nodes across all communities (total number of nodes in the network).

\[ CAcq_{globaln_i} = \sum_{k=1}^{M} \text{Encounter}_{n_i,n_k} \]  

(3)

Individuals with similar and shared interests build communities. In this paper, we assign community numbers to nodes based on their interest and mobility similarity, which is similar to LABEL [30]. Initially, community acquaintance of node \( n_i \) (global and local) remains 1 and increases once a node encounters other nodes. Values of global and local community acquaintance depend upon the number of communities and number of members in each community respectively. For example, in a network topology with 100 nodes, four communities, and 25 members in each community, the highest possible value for global and local community acquaintance can be 4 and 25 respectively. When a node encounters a node from the same community, excluding repetition, local community acquaintance is increased, but global community acquaintance remains the same. On the hand, if a node encounters a node from the different community then its global acquaintance increases.

3.2. Social activeness

The network topology of VSNs is highly dynamic, and nodes’ neighbor list frequently alters with time. As a general concept from social life, a person who meets more new people in his/her daily routine is considered to be more socially active as compared to one who keeps his/her interaction to a group of limited people. Following this concept, the social activeness of node \( n_i \) at time \( t \) can be calculated as

\[ SAct_{n_i}(t) = 1 - \frac{N_{n_i}(t - \Delta t) \cap N_{n_i}(t)}{N_{n_i}(t - \Delta t) \cup N_{n_i}(t)} \]  

(4)

where \( N_{n_i}(t) \) and \( N_{n_i}(t - \Delta t) \) represent the number of current neighbors of node \( n_i \) at time \( t \) and previous number of neighbors

of node \( n_i \) at time \( t - \Delta t \) respectively. Value of \( \Delta t \) is not constant; it depends upon the current and previous value of \( t \) at which the value \( SAct_{n_i}(t) \) is calculated.

\[
SAct_{n_i} = \beta SAct_{n_i}(t - \Delta t) + (1 - \beta) SAct_{n_i}(t) \quad (5)
\]

where \( \beta \) is a smoothing factor to consider the current value of \( SAct_{n_i} \) at time \( t \) and the previous value of \( SAct_{n_i} \) at time \( t - \Delta t \). In our proposed method, the value of \( \beta \) is set to 0.5 to consider the equal significance of current and the previous value of \( SAct_{n_i} \). A greater value for \( SAct_{n_i} \) indicates that \( n_i \) is more active in the network probability to meet new members is high. Consequently, increases the probability of packet delivery.

### 3.3. Degree centrality

Centrality is the relative measurement of nodes' importance in a social network and can be measured with different methods observed from social network analysis. However, we consider degree centrality of a node to measure its capability of direct links with its neighbors in VSNs. A higher value of degree centrality of nodes indicates the stronger capability of interaction with other nodes in VSNs and increases the probability of packet delivery. Gu et al. in [32] consider a similar concept of centrality and node activeness; however, our consideration and use of these metrics are entirely different. For a node \( n_i \), degree centrality at time \( t \) is calculated as

\[
DC_{n_i}(t) = \sum_{k=1}^{N} E_{n_i,n_j} \quad (6)
\]

Where \( E_{n_i,n_j} = 1 \) if there exists a direct communication link between nodes \( n_i \) and \( n_j \). Similar to social activeness of a node, degree centrality is periodically updated with a smoothing factor \( \beta = 0.5 \) so that the current and previous value of \( DC_{n_i} \) are equally weighted.

\[
DC_{n_i}(t) = \beta DC_{n_i}(t - \Delta t) + (1 - \beta) DC_{n_i}(t - \Delta t) \quad (7)
\]

### 3.4. SARP

Nodes within their communication range communicate in pairwise fashion and can exchange data packets. Nodes on the encounter with other nodes update their neighbor list and count their direct contacts with other nodes to update values of \( SAct \) and \( DC \). Thus, nodes on the encounter with other nodes also keep track of their community acquaintance (CAcq). Our proposed protocol, SARP, collectively combines the above three social metrics to calculate the priority value using the following equation.

\[
Priority_{n_i} = 1 - \frac{1}{CAcq_{n_i} + SAct_{n_i} + DC_{n_i}(t)} \quad (8)
\]

If node \( n_i \) encounters node \( n_j \), it compares the \( Priority \) values, and if the \( Priority \) of node \( n_i \) is greater than node \( n_j \), node \( n_i \) will forward the message to node \( n_j \) otherwise it will buffer and carry the message until a new node with higher \( Priority \) is encountered.

### 4. Simulation setup

In this section, we present the simulation setup to evaluate the performance of SARP. We used VanetMobiSim to generate vehicular mobility traces and widely-adopted network simulator NS2 to assess the performance of our proposed protocol. We compare our proposed protocol with two widely accepted routing protocols for VANETs and MANETs, i.e., GPSR and AODV. For mobility traces generation, we considered, and area of 2000 \times 3000 \text{m}^2 area near Xinghai Square\(^2\) as shown in Fig. 3. Other parameters that we used for our simulation are illustrated in Table 1. For implementation and simulation, we made the following assumption in this paper.

- All nodes are fully cooperative and cooperate in data forwarding;
- Nodes are categorized into different communities based on interest and mobility pattern.

### 5. Results and discussion

In this paper, we investigate the average End-to-end Delay and Packet delivery ratio with variation in node density with constant speed and with constant node density with varying speed. This section presents the performance analysis of SARP in comparison with AODV and GPSR.

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\(^2\) Xinghai Square is a city square in Dalian City, Liaoning Province, China. https://en.wikipedia.org/wiki/Xinghai_Square
Table 1
Simulation parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network simulator</td>
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<tr>
<td>Simulation time</td>
<td>300 s</td>
</tr>
<tr>
<td>Number of nodes</td>
<td>100, 150, 200, 250, 300</td>
</tr>
<tr>
<td>Simulation area</td>
<td>$2000 \times 3000 \text{ m}^2$</td>
</tr>
<tr>
<td>Trip generation</td>
<td>Random trip generation</td>
</tr>
<tr>
<td>Traffic source/destination</td>
<td>Random</td>
</tr>
<tr>
<td>Packets generation rate</td>
<td>5 Packets</td>
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<tr>
<td>CBR interval</td>
<td>0.20 s</td>
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<tr>
<td>MAC protocol</td>
<td>IEEE 802.11p</td>
</tr>
<tr>
<td>Speed of vehicles</td>
<td>30–70 KM/H</td>
</tr>
<tr>
<td>Transmission range</td>
<td>80 m</td>
</tr>
</tbody>
</table>

5.1. End-to-end delay

The average end-to-end delay is one of the important factors to compare the performance of any routing protocol in communication networks. The average end-to-end delay is the measurement of all possible delays from a source node to destination node, e.g., buffering, propagation, transmission, and retransmission delay. End-to-end delay is the time taken by data packets delivered successfully from a source node to destination node in a network. Average end-to-end delay can be calculated as the mean of end-to-end delays of all successfully delivered packets. We calculated the end-to-end delay as the time difference of the time at which packet was transmitted at the source and the time at which it was delivered at destination. In our analysis, we analyzed end-to-end delay for different node density and different node speed.

5.1.1. End-to-end delay vs. number of nodes

Fig. 4 shows the average end-to-end delay vs. the number of vehicles with constant node speed. We studied the end-to-end delay of our proposed protocol in comparison with AODV and GPSR. The result shows that end-to-end delay of AODV is much higher with the lower number of nodes in the network as compared to GPSR and SARP. The reasons for higher end-to-end delay of AODV are the frequent breaking of links and re-establishment of new connections. However, with increasing number of nodes, end-to-end delay is reduced, but with further increase in the number of nodes, end-to-end delay starts increasing due to increased routing overhead. On the other side, end-to-end delay of GPSR is lower than AODV. However, end-to-end delay increases with increased packet overhead caused by hello beacons in dense networks. End-to-end delay of SARP is greater than GPSR with lower node density; however, it decreases with increasing node density. With increasing node density, the probability of nodes encounters increases. Consequently, the probability of data delivery increases resulting in lower end-to-end delay. Thus, SARP outperforms GPSR and AODV in the dense network with minimized end-to-end delay.

5.1.2. End-to-end delay vs. speed

Fig. 5 shows the end-to-end delay vs. node speed with a constant number of nodes. We kept the number of nodes consistent to analyze the effect of node mobility on end-to-end delay. At lower speed with constant node density, SARP and GPSR outperform AODV. However, with increasing node speed end-to-end delay of AODV starts decreasing but with the further increasing, it starts rising again. This degradation is caused by broken link with high node mobility. On the other hand, end-to-end delay of GPSR increases with increase node speed. To compare with AODV and GPSR, SARP outperforms concerning end-to-end delay. Initially, the probability to of node encounters increases with increasing node speed. Consequently, end-to-end delay starts decreasing. However, a further increase in speed results in increased end-to-end but still outperforms both AODV and GPSR. The reason for this increase is the link failure and re-establishment of links at high speed.

5.2. Packet delivery ratio

Packet delivery ratio is another important factor to measure the performance of protocols in networks. Packet delivery ratio
depends on various parameters set for simulation which includes packet size, transmission range, the number of nodes, and node mobility. Packet delivery ratio is the ratio of the number of packets successfully delivered to a destination node to the number of packets sent by a source node. The performance is considered to better if the packet delivery ratio is high. In our analysis, we compared the performance of SARP in terms of packet delivery ratio with different node density and varying node speed.

5.2.1. Packet delivery ratio vs. node density

Packet delivery ratio of SARP in comparison with AODV and GPSR with respect to the number of nodes under constant speed is shown in Fig. 6. It is shown in the figure that with low node density, packet delivery ratio of SARP is better than GPSR but lower than AODV; however, packet delivery ratio of AODV starts decreasing with increasing number of nodes while packet delivery ratio SARP increases with increasing number of nodes. As the number of nodes increases, the probability of node encounter increases resulting in increased probability of relay nodes with a high priority value. On the other hand, packet delivery ratio of AODV and GPSR decreases with increasing number of nodes as routing overhead increases in dense networks.

5.2.2. Packet delivery ratio vs. node speed

Fig. 7 shows the effect of varying speed on packet delivery ratio with constant node density. As shown in the figure, increasing node speed has reversed effect on packet delivery ratio; however, SARP still outperforms AODV and GPSR. Initially, with the increase in speed performance of all protocols increases in terms of packet delivery ratio, however, with further increase in speed, the performance of AODV and GPSR starts immediately degrading while SARP shows better performance in terms of packet delivery ratio. Link failure at high speed causes packet loss due to which AODV performance is degraded. Similarly, very short contact duration of nodes also results in packet loss degrading the performance of GPSR and SARP. In Case if GPSR, sometimes packets may be forwarded in the wrong direction that leads to low data delivery ratio.

5.3. Impact of community acquaintance

The three social metrics we considered for our proposed model are independent. However, all these social metrics show the importance of a node in the network and play an important role in decision-making procedure to select an intermediate node for data delivery. We investigated the importance of community acquaintance in the network and performed some simulation to see the impact of community acquaintance on end-to-end delay and packet delivery ratio. We considered only degree centrality and social activeness for decision making (SARP-DC).

As shown in Fig. 8, SARP-DC performs better than AODV and GPSR in terms of end-to-end delay. However, its end-to-end delay is greater than SARP. In this case, the possible reason for this delay is that data packets are forwarded to nodes with higher degree centrality but low or no community acquaintance. On the other side, in SARP data packets are sent to the node with possible community acquaintance resulting in lower end-to-end delay.

Community acquaintance does not only help to improve the performance in terms of end-to-end delay but also increases the probability of packet delivery. As it is shown in Fig. 9, the packet delivery ratio of SARP-DC is degraded as compared to AODV, GPSR and SARP. Some of the packets are forwarded to nodes with low or no community acquaintance and are dropped as the TTL expires before reaching the destination community. Consequently, from this analysis, it is concluded that community acquaintance not only
helps to improve performance in terms of end-to-end delay but also data delivery ratio.

6. Conclusion

VSNs being a bridge between vehicular networks and social networks have attracted the research community due to its diverse range of applications. In this paper, we have presented a novel routing protocol exploiting social feature metrics, opportunistic encounters and mobility pattern for collaborative data delivery in VSNs. Traditional routing protocols based on network topology do not suit VSNs due to its highly dynamic nature. Similarly, geographically based routing protocols may result in the local optimum. The proposed protocol considers the opportunistic encounters of nodes with social feature metrics to quantify the global and local community acquaintance of nodes for selection of relay nodes.

We used VanetMobiSim for mobility trace generation considering a local area of $2000 \times 3000$ m$^2$. Extensive simulations were performed using vehicular mobility traces using NS2 to analyze the effect of node density and speed of vehicles on end-to-end delay and packet delivery ratio. We compared the performance of our proposed protocol, SARP, with two widely accepted routing protocols, i.e., AODV and GPSR. Results have shown that overall SARP outperforms AODV and GPSR in terms of packet delivery ratio and end-to-end delay. However, packet delivery ratio of SARP decreasing with increasing speed but still outperforms AODV and GPSR.

The mobility pattern of real data sets may not be the same as generated by mobility generation tools. We intend to consider real data sets of vehicular mobility to analyze the performance as a future work. Besides, emergency warning systems in VSNs demand reduced end-to-end delay and to prioritize and schedule emergency messages. Thus, we will focus on packet scheduling in VSNs. Furthermore, to enhance packet data delivery and reduce end-to-end delay we will focus on socially-aware multi-casting in VSNs with real vehicular mobility traces.

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References

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