Social-based Cooperation of Vehicles for Data Dissemination of Critical Urban Events

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Abstract—Critical urban events need to be efficiently handled, for instance, through rapid notification. VANETs are a promising choice in supporting notification of information on arbitrary critical events. Although the dynamicity of VANETs compromises the dissemination process, the connections among vehicles based on users’ social interests allow for optimizing message exchange and data dissemination. This paper introduces SOCIABLE, a robust data dissemination system for critical urban events that operates in a SloV network. It is based on vehicles’ community with common interests and/or similar routines and employs social influence of vehicles according to their network location to select relay vehicles. In a comparative analysis on NS3 with the MINUET system, SOCIABLE achieved 36.56% less packets transmitted in a dense VANET and a maximum packet delivery delay of 28ms in a sparse VANET, delivering critical event data in a real-time and robust way without overloading the network.

Index Terms—SloV, Critical Events, Recognition, Data Quality

I. INTRODUCTION

One of the main challenges on urban environments involves dealing with critical events that often arise randomly over the time and space. Critical events are commonly ones that, if not dealt with efficiently, can damage the smooth running of the city (e.g. road cracks, traffic jams) or endanger people’s integrity (e.g. fires, accidents) [1]. Vehicular Ad Hoc Networks (VANETs) naturally appear as an option for supporting those essential tasks, as vehicles embed cameras and sensors capable of detecting events, and through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications, event data can be disseminated to external entities that handle the event. Meantime, the intermittent connections between vehicles due to the high topological dynamics of VANETs, and the fact that urban area is not thoroughly covered by Base Stations (BSs) hinder data transmission, so that solutions for dissemination depend almost exclusively on opportunistic connections [2]. Moreover, the data traffic from other applications running on VANET can damage the data flow dissemination of critical events [3]. Thus, vehicles may not be willing to cooperate to save their computational resources, exhibiting selfish behavior in the network [4]. Those issues hamper the event treatment since their criticality demands a robust dissemination [5].

As part of the Cyber-Human-Systems (CHS) and Cyber Physical-Systems, the Social Internet of Things (SIoT) defines five types of object relationships: Parental (POR), relationship between devices from the same manufacturer; Co-work (C-WOR), relationship between objects that cooperate to meet an applications demands; Co-location (C-LOR), relationships between objects operating in the same location; Ownership (OOR), relationship between devices from the same user; and Social Objects Relationship (SOR), relationship between objects that come into contact sporadically or continuously. The Social Internet of Vehicles (SIoV) rose as alternative for message sharing between vehicles that hold a relationship. Usually, in SIoV, the relationships arise from the behavior of drivers, which can socialize to achieve a common goal [6]. For instance, drivers passing through the same avenue at the same time are interested on road accidents that could cause delays.

The establishment and perception of community are two techniques of social networks employed in vehicular networks [7]. We can use the temporal/spatial organization of communities to assist in the opportunistic dissemination of data from events that occur randomly in time/space. For instance, using social parameters to choose the relay nodes to forward the data can greatly influences in the dissemination performance [8], by increasing the delivery rate, decreasing the average delivery delay [9] and reducing the propensity for selfish behavior. Social Network Analysis (SNA) techniques also assist in identifying influential components to improve the efficiency of network services [10]. In the SloV context, the network may have a small number of highly influential nodes, which regulate most of the connectivity and information flow. Such influential nodes may be vehicles that have connection advantages, thus impacting the dissemination of information.

This work proposes SOCIABLE (SOCial monItoring and dissemiNAtion of urBan critical Events), a dynamic system to carry out robust dissemination of data flow from critical urban event considering the social traits of vehicles. SOCIABLE takes into account the SOR established between vehicles with common interests and/or routines to create temporary virtual communities. Communities and centrality techniques support a target dissemination by choosing relays to expedite data delivery, thus increasing user satisfaction (Quality of Experience QoE) and improving performance and robustness of events dissemination (Quality of Service - QoS). Comparative tests in the NS3 simulator against MINUET [11] showed that SOCIABLE transmitted 36.56% less packets and achieved a maximum packet delivery delay of 28ms, indicating a better network usage.

The rest of the paper is organized as follows. Section III discusses the related work. Section III describes the SOCIA-
The ubiquity of vehicles has enabled VANETs to assist in the daily lives of cities when dealing with specific urban aspects. However, solutions requiring the vehicles actively participate and cooperate in the dissemination, which does not take place in reality. For instance, devices with selfish behavior many times only cooperate in disseminating data with ones they have a strong social relationship or share a common interest in. Other solutions rely on centralized entities or overload the network with duplicate messages.

In [12], a centralized solution supports dissemination of critical event messages on VANETs aided by a server in the cloud. Despite being able to carry out the dissemination, the vehicles need to send a request and receive the response from the server. The latency of communication with the cloud increases the response time, which can compromise efficiency, especially when considering critical events. In [11], a system called MINUET monitors and disseminates urban events based on a vehicular clustering approach. Although the vehicles cooperate to forward the data to a central authority, it applies a restricted flooding strategy, which overloads the network.

Other studies have advocated the benefits of social metrics to assist in the dissemination of data for real-time scenarios. In [13], vehicles exchange messages to find out their degrees and clustering coefficients to enhance message dissemination. Although the solution guarantees the delivery of messages, it imposes a high communication cost in low density scenarios due to message caching. In [14], a social-enhanced framework facilitates data delivery with the support of social relationships of Vehicle-to-Everything (V2X) entities. Although this solution obtained satisfactory results, it depends on centralized entities (switches and a server), which imposes limitations for real-time transmissions of critical events.

The concern with selfish behaviors of network nodes has also been target in other works. In [10], a socially-aware routing mechanism stimulates selfish nodes to cooperate in data forwarding. It uses social techniques and reputation to obtain the next relay node and ensure the forward of data. However, if a node with a better reputation than the current relay is not found, it stores the data until it can find a node with a better reputation, which increases the cost of transmitting messages. In [15], a traffic management system based on crowdsensing encourages vehicles, by the means of virtual monetary incentive, to cooperate in message forwarding of abnormal events. It employs a hybrid strategy (mobile network and RSUs) for a better cost-benefit ratio. However, vehicles can help spread and not be rewarded, thus wasting resources.

III. THE SOCIABLE SYSTEM

This section describes the SOCIABLE (SOCial monItoring and disseminAition of urBan critical Events) system for collaborative monitoring of critical urban events (CUE) based on SloV (Social Internet of Vehicles). Initially we present the characteristics and infrastructure of the urban environment where SOCIABLE operates, as well as, its architecture and components. Then, we illustrate the relay selection and the SOCIABLE operation to disseminate a critical urban event.

A. SloV Environment

SOCIABLE runs on an SloV environment composed of two layers, as shown in Figure 1. The Physical Layer (PL) comprises vehicles that continuously travel on road networks and with different speeds. All vehicles communicate with other vehicles, Vehicles-to-Vehicles (V2V) or with Urban Infrastructure through Base Stations (BSs), Vehicles-to-Infrastructure (V2I), creating hybrid vehicular networks. CUEs can randomly arise in time and space. A CUE comprehends any event that impact the day-to-day life of the city and its citizens, such as fires, accidents, crimes, road obstructions, among others. These events must be usually notified to competent authorities, that mean External Entities (EE) responsible for handling events.

![Fig. 1: The SloV model](image)

The Social Layer (SL) consists of the social profiles of the vehicles built based on the social properties of the drivers (e.g., similar routines). Like any social network, nodes (vehicles) establish relationships that can be created and broken down over time. In addition, nodes with common interests or properties can be part of a community. For instance, nodes that travel on the same routes at the same schedules (same routine) are able to be part of a community to exchange messages. Any node can attend in more than one community and nodes that are part of the same community have a willingness to collaborate. Thus, some (or all) nodes in a community cooperate to perform tasks as the dissemination of data from a CUE (blue nodes in Fig. 1).

We denote an SloV composed of a set of vehicles $V = \{v_1, v_2, \ldots , v_n\}$ and a set of events $E = \{ev_1, ev_2, \ldots , ev_m\}$, so that any $v_i \in V$ vehicle can detect a $ev_j \in E$ event, as long as $ev_j$ is within the range of $v_i$. Vehicles that come into contact with each other hold Social Object Relationships (SOR), thus sharing a common profile and establishing communities. The SloV also makes a set of communities $C = \{c_1, c_2, \ldots , c_p\}$ where for any community $c_k \in C$, $c_k \subseteq V$. Therefore, $v_i \in c_k$ if, and only if, $v_i$ has the same interest/social profile as the $c_k$ community. When a $v_i \in c_k$ vehicle detects a $ev_j$ event, the formation of a set $D(ev_j) \subseteq c_k$ is initiated, defined as a subset of cooperating vehicles from $c_k$ in the $ev_j$ spread.
B. Architecture

The SOCIABLE architecture holds two modules with two components each, as shown in Figure 2. The Social Clustering Module handles the management of social communities formed by vehicles that share a SOR. The Dissemination Control Module coordinates the detection of the events and the selection of the vehicles to cooperate in the dissemination of the data of such events to the EEs.

The Social Clustering Module aims to create and maintain the social communities, and to calculate the social significance of the vehicle in its community. It consists of two components: Community Recognition and Social Influence. The Community Recognition component manages the SOR between vehicles by identifying the local community of the current vehicle. The local community are vehicles that are part of the same community as the current vehicle and are directly connected to it (neighbors). This is important because only vehicles belonging to the local community can cooperate to disseminate the event. Every $v \in V$ periodically transmits beacons containing its identification (id), current position (pos), number of neighbors (n.Nbr), and social profile (profile(v)) to build community knowledge. When a vehicle $v_i$ receives a beacon from a vehicle $v_j$, it checks whether \( \text{profile}(v_i) = \text{profile}(v_j) \). If so, it stores $v_j$ in its list of neighbors willing to cooperate (nbrList($v_i$)). The beacons are constantly exchanged to assist the community maintenance.

The Social Influence component deals with the social importance the current node has in the community, hence to its neighborhood. By means of the nbrList and social metrics, this component calculates which neighbors are more likely to cooperate based on their social parameters. In this work, we employ the Structural Influence (STR) metric, which denotes how influential a node is based on its current position. As more influential a node is, higher its contribution on the data dissemination efficiency [16].

The Dissemination Control Module addresses the detection of the CUE, the selection of the cooperative vehicles and the forwarding of the event data flow to the EE. This module consists of the Detection and Selection components. The first one detects and starts the monitoring of the events. In this way, when a given $vd$ vehicle is inside range of a $ev$ event, $vd$ automatically assumes the role of Detector and collects the context data of $ev$, which are: instant detection time, location, speed and direction. For the sake of simplicity, we assume that the analysis and detection of the CUE take place through image processing and analysis techniques obtained by sensors from cameras embedded in the vehicles. We also assume that during the event analysis, the Detection component estimates the Time-to-Live (TTL), which is the maximum number of hops over a message can be propagated.

When obtaining the context information of the event, the Selection component starts the process of defining the other two roles that nodes can play during the cooperation for the dissemination, which are: (i) Relay: the vehicle responsible for forwarding the event data flow in the neighborhood, in addition to selecting the next relay node; (ii) Gateway: vehicle that delivers the data about the monitored event to BS and, consequently, to EE. Considering the current node as the $vd$ detector node, the $c_k$ community and that $vd \in c_k$, $vd$ assumes as possible collaborators the nodes that are part of $c_k$. Thus, $\forall v_i \in c_k$, if $v_i$ is within reach of a BS, then $v_i$ is gateway. If $v_i$ has the highest STR among all neighbors of $vd$ in $c_k$, then $v_i$ is relay. It is important to note that both the $vd$, after detecting an event, or any $v_i$ that has been selected as relay, can initiate the selection process. Once the relay is selected, $vd$ (or $vi$) generates monitoring packets and broadcasts them in the neighborhood. It also informs the $id$ of the next selected relay node. In addition, when $vd$ (or $vi$) is within reach of a BS, it delivers the event data to the BS.

Algorithm 1 Detection and dissemination

\begin{verbatim}
Input: msg.Mon(ev)
/* nbrList(v) is the list of neighbors of v in the community */
1: if ev is in v_i’s range then
2: ud ← v_i
3: ud creates msg.Mon(ev);
4: end if
5: if TTL > 0 then
6: if v_i is within a BS’s range then
7: v_i is gateway
8: v_i delivers msg.Mon(ev) to BS
9: end if
10: if (v_i == vd) or (v_i == vr) then
11: for each vehicle $v_j$ in nbrList($v_i$) do
12: check STR of $v_j$
13: end for
14: vr ← $v_j$ with the highest STR
15: $v_i$ disseminates msg.Mon(ev) in the neighborhood
16: end if
17: else
18: discards msg.Mon(ev)
19: end if
\end{verbatim}

Algorithm 1 describes the SOCIABLE operation when a $v_i$ vehicle detects a $ev$ event or when $v_i$ receives a msg.Mon(ev) monitoring message. When $v_i$ detects $ev$, it starts to act as the $vd$ detector vehicle and creates msg.Mon(ev) (lines 1–4). Regardless of whether $v_i$ received or created msg.Mon(ev), $v_i$ checks that its TTL has not yet expired (line 5). Case the TTL has expired, $v_i$ discards the message. Otherwise, $v_i$ checks whether it is within range of an BS. If so, then $v_i$ plays as gateway, thus delivering the message (lines 6–9).
If \( v_i \) is \( vd \) detector or \( vr \) relay (line 10), then \( v_i \) initiates community recognition. Upon recognition, \( v_i \) checks which of its neighbors has the highest \( STR \). This neighbor is then informed it is the next \( vr \) relay. Finally, \( v_i \) disseminates \( msg_Mon(ev) \) (lines 11–17).

C. Relay selection

SOCIABLE employs a strategy to achieve QoS and QoE gains when selecting the relays. QoE values are based on social benefits the devices offer, which are perceived by employing SOP. SOCIABLE chooses as the next relay the neighbor node with the highest \( STR \), which is calculated according to Equation [1][16]. It makes use of four centrality metrics: (i) Betweenness Centrality (BC), corresponds to how many times a node is on the shortest path between all pairs of nodes; (ii) Closeness Centrality (CC), denotes how close a node is to all other nodes; (iii) Degree Centrality (DC), is the number of nodes directly connected to a node (i.e. its neighbors); (iv) Eigenvector Centrality (EC), corresponds to how many important nodes a node is directly connected to. In this work, we assume important nodes as those that directly reach BSs (i.e. gateways). Each metric has an associated weight (\( W \)) and the sum of the four weights is 1.

\[
STR_i = W_{BC} \cdot (BC)_i + W_{CC} \cdot (CC)_i + W_{DC} \cdot (DC)_i + W_{EC} \cdot (EC)_i \tag{1}
\]

The first three metrics usually improve QoS, since choosing a node with better \( BC, CC \) and \( DC \) values increases the probability in delivering the data [2], while the \( EC \) metric influences the QoE since if the data reaches the gateway quickly, the user satisfaction increases. Thus, when a detector vehicle selects the next relay to forward the packet, it gives more importance to QoS (higher \( W_{BC}, W_{CC} \) and \( W_{DC} \) values) and less to QoE (lower \( W_{EC} \) value). As the next relays are chosen, the influence of QoS decreases while QoE increases. Figure 3 illustrates the relay selection process. When \( vd \) detects a event, \( vd \) chooses the next relay by applying a higher weight to QoS than QoE (\( w_p > w_q \)). As the next relays are chosen, \( w_p \) value decreases while \( w_q \) value increases. This process continues until the packet reaches a gateway.

D. Operation

Figure 4 illustrates SOCIABLE’s operation when detecting an \( ev \) event. In the example scenario, we have the set \( V = \{v1, v2, v3, v4, v5, v6, v7\} \) and a BS to assist in the \( ev \) data transmission. We have also established two communities \( C1 \) and \( C2 \) formed by green and blue vehicles, respectively. In this way, when \( v1 \) detects \( ev \), it simultaneously starts the community recognition and monitoring step, thus it creates a \( P \) packet with a \( TTL = 3 \) value, which limits the number of transmissions of \( P \). During community recognition, \( v1 \) finds that, among its neighbors, only \( v3 \) is part of its \( C1 \) community. Thus, regardless its \( STR \) value, \( v3 \) is chosen as the next relay. Whereas with each \( P \) transmission, its \( TTL \) decreases by one unit, so that when \( v3 \) receives \( P \), its \( TTL = 2 \), which means that \( v3 \) can then retransmit the \( P \) packet.

![Fig. 4: Example of the SOCIABLE operation](https://github.com/fcodeca/LuSTScenario)

Fig. 4: Example of the SOCIABLE operation

When relaying \( P \), \( v3 \) discovers that it has two neighbors, \( v4 \) and \( v6 \), in \( C1 \). Among them, \( v3 \) chooses the one with the highest \( STR \), thus being able to reach more nodes in the network. In this case, we consider \( v6 \) (\( STR = 12 \)) as the node with the highest \( STR \), thus being chosen as the relay. \( v3 \) then transfers \( P \) to \( v4 \) and \( v6 \). As \( P \) is retransmitted, the relay increases the weight (influence) of the QoE indicator while decreasing the weight of QoS indicator. Since \( v4 \) is not a relay, nor is within reach of a BS, it discards \( P \). On the other hand, \( v6 \) is within reach of a BS (gateway), then it delivers \( P \). In addition, since \( v6 \) is also a relay, it passes \( P \) to \( v7 \). Finally, although \( v7 \) is also within reach of a BS, it finds that the \( TTL \) of \( P \) has expired (\( TTL = 0 \)), thus discarding \( P \). In this example scenario, as the relay nodes are chosen, the group \( D(ev) = \{v1, v3, v6, v7\} \) is established, which are the vehicles that cooperated to disseminate the event data.

IV. Evaluation

We evaluate SOCIABLE to assess its efficiency and robustness in monitoring and disseminating the data flow of critical urban events, as well as, the social aspects of the system and their influence and benefits to the dissemination. We have implemented and tested in the NS3 simulator, version 3.28, together with SUMO. We also made use of the LuST project (Luxembourg SUMO Traffic), a real traffic mobility scenario [1]. The simulations were carried out in two different scenarios, considering one event, different numbers of traffic lanes, direction of the road and number of vehicles traveling. We set up a single fixed event with a total duration of 8 minutes. We take into account communities formed by vehicles that realize the same routine. That is, being a vehicle \( v \), a time interval \( \Delta t \) and an area \( a \), we have that \( v(\Delta t, a) \) denotes that the vehicle \( v \) is in the area \( a \) in the interval \( \Delta t \). Thus, two vehicles \( v_i \) and \( v_j \) establishes a SOP relationship when \( v_i(\Delta t_i, a_i) == v_j(\Delta t_j, a_j) \). Therefore, we use a vehicle relationship rate of 90%. That is, 90% of the vehicles in the

1[https://github.com/fcodeca/LuSTScenario]
test scenarios are part of the community. Despite being a high rate, it can be achieved if we consider drivers who travel on a stretch of road at the same time, for example, when taking their children to school. We compared the performance of SOCIABLE with MINUET, which is a solution that does not contemplate social characteristics.

### Table I: Simulation setting

| Parameter                        | LD          | HD          |
|----------------------------------|-------------|-------------|
| Simulation time                  | 9 mins      | 9 mins      |
| Event duration                   | 8 mins      | 8 mins      |
| Kind and number of lanes         | one-way / 3 lanes | two-way / 6 lanes |
| Transmission range               | 100 m       | 100 m       |
| Number of vehicles               | 91          | 754         |
| Number of base stations          | 1           | 1           |

Table I shows the parameters applied in the simulations for low density (LD) and high density (HD) scenarios. We assess the SOCIABLE efficiency through the following metrics: Number of Collaborating Vehicles (NCV), which indicates the amount of vehicles (detector, relay and gateway) that collaborated to the dissemination; Average Delivery Delay (ADD), which denotes to the time interval between the instant the event is detected and the first monitoring packet is delivered to the BS; Number of Generated Monitoring packets (NGM), which indicates the total amount of monitoring packets generated by the detecting vehicles; Number of Delivered Monitoring packets (NDM), which corresponds to the total amount of monitoring packets delivered to the BS; Exchanged Packet Overload (EPO), that means the communication cost (beacons and monitoring packets exchanged) by running SOCIABLE. To evaluate the SOCIABLE social behaviour, we assessed the STR metric, which encompasses four other social metrics, as explained in Subsection III-C. Over the relays’ selection, we increased the QoS social metric weights from 0,1 to 0,9 and decreased the QoE social metric weight from 0,9 to 0,1.

### A. Results

This section presents the analysis of the tests carried out to evaluate the performance of SOCIABLE compared to MINUET, in addition to SOCIABLE’s social behavior. The graphs in Figure 5 show the number of vehicles collaborating in the dissemination event data over time (NCV), which indicates the amount of vehicles (detector, relay and gateway) that collaborated to the dissemination: Average Delivery Delay (ADD), which denotes to the time interval between the instant the event is detected and the first monitoring packet is delivered to the BS; Number of Generated Monitoring packets (NGM), which indicates the total amount of monitoring packets generated by the detecting vehicles: Number of Delivered Monitoring packets (NDM), which corresponds to the total amount of monitoring packets delivered to the BS; Exchanged Packet Overload (EPO), that means the communication cost (beacons and monitoring packets exchanged) by running SOCIABLE. To evaluate the SOCIABLE social behaviour, we assessed the STR metric, which encompasses four other social metrics, as explained in Subsection III-C. Over the relays’ selection, we increased the QoS social metric weights from 0,1 to 0,9 and decreased the QoE social metric weight from 0,9 to 0,1.

### Fig. 5: Vehicles collaborating in the dissemination

The graphs in Figure 7 show the number of monitoring packets created (NGM) when the event is detected and monitoring packets delivered (NDM) to the BS, over the number of collaborating vehicles (NCV) in SOCIABLE and MINUET. In both scenarios, SOCIABLE and MINUET obtained same NGM values, despite fewer vehicles collaborated in SOCIABLE. This is because there are the same number of detecting vehicles. In LD scenario, SOCIABLE achieved a NDM value higher than MINUET when there are fewer vehicles collaborating. As more vehicles collaborate, MINUET delivers more packets than SOCIABLE. In HD scenario, SOCIABLE achieved a higher NDM than MINUET only when two vehicles collaborate. Furthermore, MINUET delivered packets with up to 14 collaborating vehicles. The number of vehicles collaborating is higher in MINUET because it uses flooding, whereas SOCIABLE uses social parameters to choose one relay only, which reduces the number of copies of packets traveling on the network. Results indicate that SOCIABLE and MINUET are able to detect and deliver monitoring packets of urban events to the BS under different network and
traffic conditions. The results also attest the higher efficiency in resource utilization of SOCIABLE, since fewer vehicles collaborate to deliver similar amount of monitoring packets. It delivers data from critical urban events to external entities by the means of communities created from the social relations between the vehicles. Simulations results demonstrated that SOCIABLE selects vehicles that cooperate in the event dissemination and deliver messages to the base station in real time. Also, it disseminates the data throughout the event duration in a robust fashion. A comparison showed that SOCIABLE transmitted 36.56% less packets and achieved a maximum delivery delay of 28ms. As future work, we plan to analyze SOCIABLE’s performance under events overlapping in time and space and to apply other community mechanisms.

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