Data Dissemination in Vehicular Networks using Context Spaces

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***Abstract*—A data dissemination process to support Vehicular Clouds poses a series of challenges, when there is no central entity aware of all the nodes' subscription. Each individual node (i.e., a car) can subscribe to different topics (i.e., according to the applications currently being executed), and can only be aware of its own interests and those of a node it is in contact with, if any. In this paper, we propose *Vehicular ONSIDE*, an extension of our previously-proposed ONSIDE algorithm, particularly adapted for opportunistic data dissemination in Vehicular Ad-Hoc networks. Advancing location-based vehicular dissemination algorithm, Vehicular ONSIDE leverages a node's online social connections (i.e., friends on social networks such as Facebook or Google+), its interests and the history of contacts, and other context information, in order to decrease congestion and required bandwidth, while not affecting the overall network's hit rate and the delivery latency. We present evaluation results for the algorithm, using OMNET++, that demonstrate the capability of the algorithm to cope with highly dynamic vehicular ad-hoc networks.**

I. Introduction

The next five years (from 2015 to 2020) are predicted to usher in the biggest growth of the Internet yet. Gartner predicts 25 billion new devices will be added to the Internet by 2020 [1]. Cisco predicted 50 billion earlier but has revised it downward to 36 billion including a quarter billion new Internet-enabled vehicles. Internet-equiped vehicles are ideal observation platforms for their surrounding environment, as they can memorize a large degree of detail and can store relevant local information - previous studies show that it is very likely that a driver entering the city restaurant district can get restaurant recommendations directly and with more content from vehicles in the neighborhood than from the web [1]–[3]. "Vehicular Cloud Computing" is the new paradigm coined to describe vehicle-based interaction and collaboration, done to sense the environment [1].

[1] http://www.information-age.com/technology/mobile-and-networking/123458905/gartners-internet-things-predictions

Cloud-inspired on-demand access to information is vital to modern urban life. Cities transform more into all-connected systems of systems, where citizens can access and use, and become creators and curators of vital information (e.g., public transport schedule, data on congestions or scheduled maintenance work, information about accidents, threats, monitored data about poluttion, noise, etc.). But the huge volume, velocity and variety of information becoming available, leads to access to information in urban environments becoming an ever more complex process. Thus, the traditional Cloud-centered access model needs to be augmented with alternative ad-hoc means – i.e., get data 'on the premises', from 'proximity' mobile devices. This is where vehicular ad-hoc networks come into place. When an accident takes place, cars can disseminate faster information to warn other drivers through direct contacts.

Lately, Opportunistic Networks (or OppNets) have been a main focus of research in the area of mobile networks. They are composed almost entirely of mobile devices that communicate between each other using a store-carry-and-forward (SCF) paradigm. This means nodes are only able to communicate when they are within wireless range of each other. Whenever a destination is not directly accessible, a source opportunistically forwards data to (some of) its neighbors. Disconnections between nodes are the norm in opportunistic networks, so forwarding and dissemination algorithms should make the most of a contact, especially if the network is sparse and nodes do not meet often. For data dissemination in particular, OppNets use channels of communication: messages are broadcast, or published, on channels to which all interested nodes must subscribe. Data dissemination in OppNets is a difficult problem, because the network is highly dynamic: users continuously appear and disappear from the network, thus publishers and subscribers might be completely unaware of each other, and they might never even connect at the same time to the same part of the network. Moreover, there is no central entity that is aware of all the nodes' subscriptions. Instead, each node is only aware of its own interests and those of a node that it is contact with. Therefore, data should be moved and replicated in the network in order to be carried to interested users in spite of disconnections and partitions.

Content-based networking is a fundamental paradigm for Vehicular Clouds as well, because new content is continuously added and replicated across vehicles, without a central directory [1]. In the lack of a central authority, distribution of (and access to) content must be controlled somehow via the intrinsic mobile cloud social structure. Associated with content search is the caching of data at intermediate nodes following the search. The cached data can efficiently satisfy future searches for the same content, and is the foundation for efficient content based routing.

We previously proposed ONSIDE (OpportuNistic Socially-aware and Interest-based DissEmination), a dissemination strategy that leverages information about a node's social connections, interests and contact history, in order to decrease network overhead and congestion, while improving hit rate and delivery latency [4]. This is done by carefully selecting the nodes that act as forwarders, instead of simply flooding every node. We have shown that ONSIDE is able to provide superior performances for disseminating information in people-centric ad-hoc +networks [4]. However, our working hypotheses change in case of information dissemination in Vehicular Clouds and Vehicular Ad-Hoc Networks (or VANETs - the network infrastructure on top of which Vehicular Clouds are built). A VANET is a multi-hop ad-hoc network composed of vehicles that communicate among them by exploiting wireless technologies (typically) belonging to the 802.11 family. This is a specialization of the multi-hop ad-hoc network paradigm well motivated by the socio-economic value of advanced Intelligent Transportation Systems (ITS) aimed at reducing traffic congestions, the high number of traffic road accidents, etc.

Message dissemination, in particular, can lead to ITS applications in which cars directly exchange traffic information about road congestions, construction/accident sites or other safety-related events. However, VANETs introduce unique challenges for achieving robust message dissemination, different than conditions in people-centric OppNets [5]:

- *VANETs are unbounded networks*. Large-scale networks and large-scale movement are major implications behind the unbounded nature of VANETs. We cannot suppose any vehicle is capable to directly collect sufficient information about traffic participants. Thus, *context information should be collected and used in the dissemination strategy, combined as much as possible from all traffic participants*.
- *VANETs have their own unique mobility patterns*. Vehicles tend to move on specific trajectories, but they are short-lived. This semi-structured short-life mobility patterns increase the difficulty of delivering messages to all intended receivers with minimum packet overhead in the highly dynamic VANET environment. Thus, *a dissemination strategy should not address each vehicle separately, but instead address at-front delivery towards the dissemination channel and node's interest.*
- *VANETs are composed of sparse and uneven groups of vehicles*. Partitions and congestions are very common in VANET wherein vehicles are often distributed unevenly. Partitioning in VANET imposes serious challenges to robust message dissemination, i.e. messages cannot be easily delivered across the partitions. However, *combining context with social information can optimize the dissemination strategy, by sending data to cars belonging to various social groups*.

We propose Vehicular ONSIDE (Vehicular OpportuNistic Socially-aware Interest-based DissEmination), a unified dissemination strategy for both interest- and location-centric messages, extending our previously proposed ONSIDE scheme [4]. The algorithm leverages information about a node's social connections, encounters, interests and mobility patterns to disseminate messages of both types.

The rest of the paper is structured as follows. Section II presents related work. Section III presents the proposed dissemination strategy, and in Section IV we analyze experimental results. Section V concludes the paper.

II. Related Work

OppNets have been an important research topic in the area of mobile networking in recent years, mainly due to the ubiquitousness of mobile devices of all shapes and sizes. However, the focus has mainly been on routing and forwarding, where a message is sent from a single source node to a unique destination, as opposed to data dissemination, where nodes subscribe to channels that publish data. A thorough analysis of opportunistic networking was done by Conti et al. [6], who analyze functions such as message forwarding, security, data dissemination and mobility models.

Since data dissemination presumes sending a message to multiple nodes, Epidemic [6] has been employed in such situations. The algorithm simply floods the network with a message until it reaches all interested subscribers. When two Epidemic nodes meet, they exchange all the messages they carry between each other. This way, assuming that a node can store an unlimited number of messages in its data memory, the maximum hit rate of the network is guaranteed. However, flooding the network with messages can very easily lead to congestion and high overhead, especially in dense networks with high publishing activity.

Data routing and dissemination algorithms have evolved along the years, from simple flooding solutions such as Epidemic, to more complex algorithms that use social metrics, contact prediction or history analysis. However, such solutions are used for routing, whereas in [4] we proposed ONSIDE, designed to offer a publish/subscribe solution. ONSIDE has the advantage of using context information of various types (such as social knowledge, contact history, nodes' interests) with the purpose of reducing congestion and achieving high hit rates. We previously showed that ONSIDE is able to reduce congestion without affecting the hit rate and delivery latency.

However, in vehicular ad-hoc networks (VANETs), mobility and networking conditions are different than what happens within people-centric ad-hoc networks [6]. While ONSIDE and other protocols are designed for information dissemination in relatively-static human-formed networks, in VANETs nodes are highly mobile and have a tendency to cluster. The high level of vehicles' mobility and the possibility of sparse networking scenarios, which occur when the traffic intensity is low, make inefficient legacy store-and-forward dissemination paradigms used in OppNets, and push toward the adoption of the more flexible, pragmatic and robust store-carry-and-forward paradigms [6].

Data dissemination and routing methods for VANETs were previously proposed, but they rely mostly on geocast/broadcast and multicast [7]. Such methods mostly rely on location services to enforce their scope; location is an on-board sensed contextual data that is used to make informed decisions. We extend this, by observing that drivers have also a social-dimension; they are creators and consumers of content that is being routed or disseminated. Drivers have social connections and interests of their own. Content is being requested most likely at the interest of the driver ('I want to receive specific POIs in this town'), and when a social sibling is present ('I only trust information coming from colleagues and friends'). The use of social aspects is not entirely new (see [8], and we previously used it in [4]), but little was used in the context of VANETs.

Thus, *Vehicular ONSIDE* enhances the traditional OppNets data interest-based and socially-aware dissemination strategy for VANETs, by actively using in the dissemination decision the node's context, together with traditional contextual data (i.e., location), as explained in the following Section.

III. Vehicular ONSIDE

ONSIDE proposes an interest-based and socially-aware dissemination strategy that takes advantage of the fact that nodes that have common interests (i.e. that are subscribed to the same channels), or are socially-connected, tend to meet each other more often than nodes that do not. This happens because humans generally form groups (i.e., communities) based on similar tastes and preferences, since people sharing common interests are more likely to bond together.

Whenever two nodes running ONSIDE meet, they exchange lists of messages in their data memory (characterized by unique IDs and channel information) and lists of topics each node is interested in. Based on this information, each node analyzes the other node's messages and decides which of them should be downloaded. It then sends a download request for those messages, and starts downloading them one by one until it finishes, or until the two nodes are no longer in contact.

The ONSIDE dissemination strategy requires the messages to be interest-centric. In vehicular OppNets, messages (e.g., traffic information) can be modelled by creating distinct interests. However, many ITS systems usually require messages to also be locality-based (i.e., a traffic congestion announcement is of no interest to cars located too far from the actual congestion; for these cars, the congestion conditions can change by the time they might reach that area, thus rendering the dissemination of such information to them useless).

In *Vehicular ONSIDE*, a node A uses the following function to analyze a message M from an encountered node B, and to decide whether it should be downloaded:

$$\begin{aligned} &exchange(src, dst, msg) = \\ &\quad similar\_node\_contexts(src, dst) \\ &\quad \wedge (node\_interested(dst, msg.context) \\ &\quad \vee intr\_friends(dst, msg.context) \geq thr_{friends} \\ &\quad \vee intr\_enc(dst, msg.context) \geq thr_{encounters}) \end{aligned} \tag{1}$$

where $similar\_node\_contexts : Nodes \times Nodes \rightarrow \{0, 1\}$ determines whether the contexts of the nodes are similar, $node\_interested : Node \times Contexts \rightarrow \{0, 1\}$ determines whether the context of the message is similar to that of the node, $intr\_friends : Nodes \times Contexts \rightarrow \mathbb{N}$ determines the number of friends of the node whose contexts are similar to that of the message and $intr\_enc : Nodes \times Contexts \rightarrow \mathbb{N}$ determines the number of encounters of the node whose contexts are similar to that of the message.

A. Context Spaces

The *Vehicular ONSIDE* exchange function (1) depends on comparing node and message contexts. We model context using the mathematical theory of context spaces [9], a modelling approach that provides abstractions for context-aware applications in need to react and adapt to their environment.

A *context attribute* (denoted as a_i) is a fundamental descriptive component of the context, whose data type depends on the associated sensor, virtual or physical. For example, location can be represented as a context attribute, consisting of a tuple of two real numbers (i.e., latitude and longitude). A context attribute can be single- or multi-valued, depending on the associated sensor. An attribute attached to a physical sensor is a single-valued attribute (e.g., temperature). Unlike physical sensors, virtual sensors can be associated with multi-valued attributes (e.g., interests of a user).

An *application space* (denoted as $\mathfrak{R}$) is a tuple whose members represent the domain of values (denoted

$Dom(a_i)$) of every context attribute defined within an application:

$$\Re = (Dom(a_1), Dom(a_2), ..., Dom(a_N))$$

For example, an application space for a system that contains only the location as a context attribute, is the following:

$$\begin{aligned}\Re &= (Dom(location))\\ Dom(location) &= \{(lat, long) | lat \in [-90°; +90°]\\ &\wedge long \in [-180°; +180°]\}\end{aligned}$$

A *situation space* (denoted as S_j) is a tuple whose members represent acceptable regions of values (denoted a_i^R) for every context attribute:

$$S_j = (a_1^R, a_2^R, ..., a_N^R)$$

where $a_i^R = \{a_i^V | P(a_i^V)\}$. For example, a situation space for a system that contains only the location as a context attribute and that covers only the tropical region is the following:

$$\begin{aligned}S_{tropical} &= (location^R)\\ location^R &= \{(lat, long) | (lat, long) \in Dom(a_i^V)\\ &\wedge lat \in [-23.27°; +23.27°]\}\end{aligned}$$

Context attributes may be marked as optional within situation spaces using a syntax similar to (2). An attribute marked as optional is not required to be within the acceptable region for the situation to be inferred.

$$S_j = (a_1^R < required >, ..., a_N^R < optional >) \tag{2}$$

A *context state* (denoted C_j) is a tuple whose members represent context attribute values (denoted as a_i^V):

$$C_j = (a_1^V, a_2^V, ..., a_M^V))$$

For example, a context state for a system that contains only one context attribute, location, would be the following:

$$\begin{aligned}C_j &= (location^V)\\ location^V &= (44.441194°, 26.051923°)\end{aligned}$$

The *containment operator* ('∈' in (3)) can be applied to decide whether a context state is contained within a situation space. Given a context state C_j and a situation space S_k, the containment of the state in the space depends on the containment of each context attribute value of C_j in the coresponding region from S_k:

$$C_j \in S_k \leftrightarrow a_i^V \in a_i^R \forall i \tag{3}$$

The containment of a multi-valued context attribute inside a region implies the containment of at least one of its values in the region:

$$a_i^{MV} \in a_i^R \leftrightarrow \exists a_i^V \in a_i^{MV}, a_i^V \in a_i^R$$

The application spaces can be represented as multidimensional Euclidean spaces, where each domain of values $Dom(a_i)$ corresponds to a dimension, and subspaces sometimes intersect but none contains the others. Although the containment operator is applicable in this case, declaring the subspaces as not contained one within any of the other, a more versatile model would define a new possible relationship, partial containment $\widetilde{\in}$:

$$\begin{cases} C_j \in S_k & \text{fully contained, } \lambda = 1\\ C_j \widetilde{\in} S_k & \text{partially contained, } \lambda = 0\\ C_j \notin S_k & \text{not contained, } \lambda \in (0; 1) \end{cases} \tag{4}$$

In (4), λ represents the *degree of containment* of a subspace within the other, or of a context state within a situation space. In a 3-dimensional Euclidean space, the degree of containment of two 3-dimensional subspaces can be the ratio between the volume of the intersection of the two objects and the volume of the containing object.

Finally, the *degree of similarity* enhances the containment operator, enabling the identification of partially contained states, reflecting how well a certain state relates to a situation space. This parameter relies on the Euclidean distance between vectors' attributes, and is defined as:

$$Diff_i^a = \begin{cases} 0 & \text{all types, inside region}\\ (a_i^V - \widetilde{a}_i^V)^2 & \text{numerical, outside}\\ 1 & \text{non-numerical, outside} \end{cases}$$

where $\widetilde{a}_i^V$ is the average value of the region a_i^R.

In this case, the numerical context attributes are normalized as:

$$\text{Degree of Similarity} = \left(\sum_{i=1}^{N} (1 - Diff_i^a)\right) / N$$

Non-numerical context attributes rely on boolean numbers to express the difference between a value and a region. Although this approach might work for simple attributes (e.g. interests), it limits the precision of the computed difference and degree of similarity for more complex attributes (e.g. history-based location). A different approach, that overcomes the previous limitation, is to use a function $f_i^a : Dom(a_i) x 2^{Dom(a_i)} \rightarrow [0; 1]$ for non-numerical attributes, to determine a fuzzy difference value:

$$Diff_i^a = \begin{cases} 0 & \text{numerical, inside region}\\ (a_i^V - \widetilde{a}_i^V)^2 & \text{numerical, outside region}\\ f_i^a & \text{non-numerical} \end{cases}$$

where $\widetilde{a}_i^V$ is the average value of the region a_i^R, and $f_i^a : Dom(a_i) \times 2^{Dom(a_i)} \rightarrow [0; 1]$.

The degree of similarity assumes that the context attributes are of the same importance, using a $1/N$ weight for each attribute. In practice, different weights may be assigned to reflect the importance of a context attribute relative to others in the situation space:

$$\text{Weighted Deg. Sim.} = \sum_{i=1}^{N} \left((1 - Diff_i^a) * w_i\right) \tag{5}$$

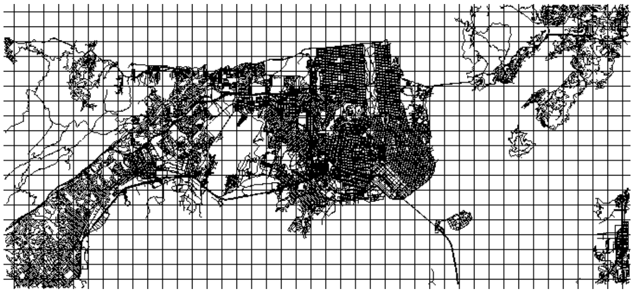

Figure 1. Tiled map.

where $\sum_{i=1}^{N} w_i = 1$.

B. Context Spaces in Vehicular ONSIDE

Vehicular ONSIDE uses the node's context, with community information, in the data dissemination algorithm decision process (1). The node's context (i.e., its interests and location), are modelled as context attributes.

We assume a node can subscribe to multiple topics. We use non-numerical multi-valued context attributes to represent the subjects of interest for nodes. Such attributes are considered to be within acceptable regions if at least one of their values is contained in it.

Secondly, location is used as a context attribute of messages, thus allowing them to be bound to certain geographical areas. For a node, we model location as a multi-valued attribute that retains the most frequently visited neighbourhoods, each one associated with the number of visits. Thus, nodes retain a location history that is used to extrapolate a mobility pattern. Messages bound to a certain area are spread to all nodes that frequent relatively close neighbourhoods.

For describing location, we adopt a tiled model (similar to [10]). The map is split into a grid of cells (see Figure 1), which are the elementary positions used by *Vehicular ONSIDE*. Whenever a vehicle passes from one tile to another, it increases the latter's visit counter. The counters can then be used to compute the probability of the vehicle to visit a certain area:

$$P(tile_{ij}) = \frac{visits(tile_{ij})}{\sum_{k=0}^{N} \sum_{l=0}^{M} visits(tile_{kl})}$$

Based on this probability, the relevance of a message is determined as

$$R(msg) = max\{P(tile_{ij}) * f(ndist(msg.location, tile_{ij}))\}$$

where $ndist(tile1, tile2) = NMD(tile1, tile2)$, and $f(x) = 1 - x^2$.

The normalized Manhattan distance (*NMD*) can be replaced by any other distance, such as Euclidean, as long as it is normalized. The function f controls the decrease of the probability and message relevance with the increase of distance, and is correlated with the size of the tiles (as the area size defining a tile increases, the function should decline more rapidly). The second degree polynomial softens the decrease for relatively close tiles.

The nodes further retain the relevant attributes organised as context states, while situation spaces are used for data. An exchange takes place when the contexts of the two encountering nodes are similar, considering the containment operator (their situation spaces should include acceptable overlapping regions for their attribute values). Even if contained, a message is only exchanged if it is also relevant for the node (or for the community), where relevance is computed by checking if the state of the node is contained in the situation of the message.

The containment of a context state in a situation space is an important aspect of the modelling approach, as its precision casts a direct influence over the efficiency of the dissemination algorithm. The usage of a strict comparison (containment operator) could lower the hit rate, while a loose comparison could increase the bandwidth usage. In addition, some attributes can be more important than others when trying to infer a situation. As a result, the Weighed Degree of Similarity (5) is used to determine whether a state is contained in a situation or not. Every situation declares its own weights for the attributes and its own similarity threshold, enabling the control of the dissemination of each type of message.

IV. Experimental results

We evaluated *Vehicular ONSIDE* using realistic mobility trace simulation. We used the Omnet++ network simulator, due to its extensibility and modularity. The environment for our simulation was generated using OpenStreetMap. Also, we used the open-source framework for running vehicular network simulations called Veins, and Simulation of Urban Mobility (SUMO), a microscopic road traffic simulation package designed to handle large road networks. Thus, we were able to perform bidirectionally-coupled simulation of road traffic and network traffic. Movement of nodes in Omnet++ simulation is determined by movement of vehicles in road traffic simulator SUMO. Nodes can then interact with the running road traffic simulation.

We assumed the use of vehicular wireless communication protocols such as IEEE 802.11-based extensions for Intelligent Transportation Systems (ITS) applications (i.e., IEEE 1609, IEEE 802.11p, or even the lower quality IEEE 802.11a). Several studies showed how such protocols behave under real-world traffic conditions and different application and context requirement [11] [12], and as such vehicles can communicate with others (i.e., vehicle-to-vehicle) in ranges $[200m; 500m]$ [13].

We simulated different scenarios using the mobility dataset collected in San Francisco [14]. The territory of San Francisco, California covers an area of about $121km^2$. We simulated the movement of all 536 cabs in the datasets, over a period of approximately 24 days. We divided the San Francisco map (with an area of $50km \times 50km$) into a 25×25 grid of tiles (leading to tiles of $\approx 2000m \times 2000m$).

Vehicular ONSIDE relies on the social connections and on the node interests. Social data and interests were generated – we used a Power-law distribution to model

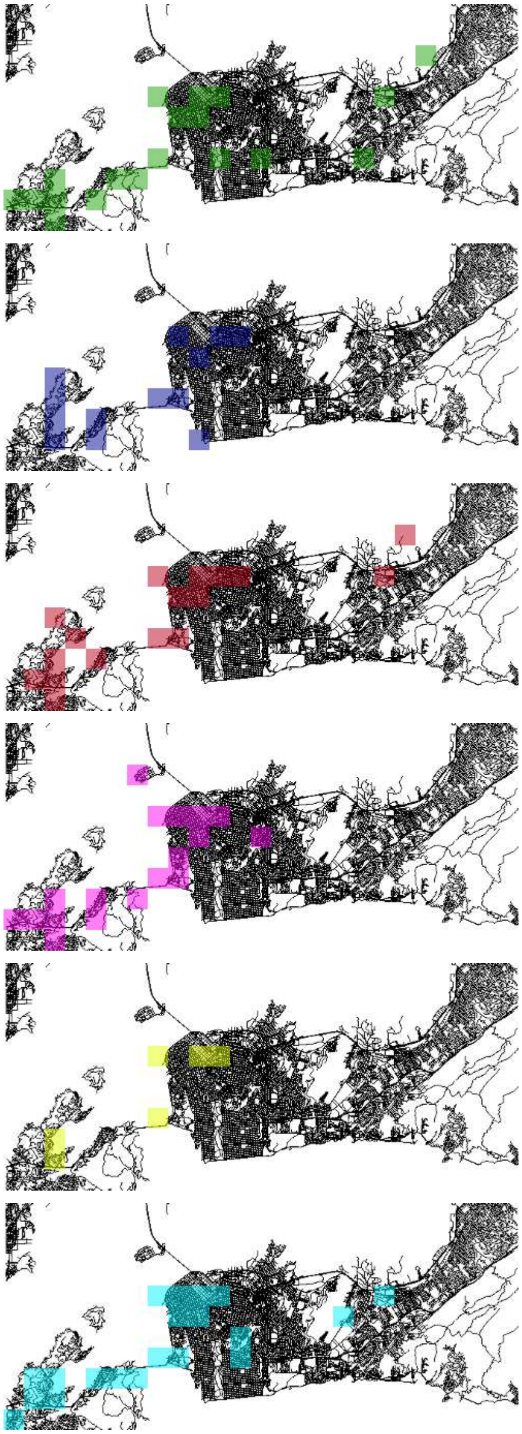

Figure 2. Interest maps for: books, magazines, movies, music, sports and tv-shows.

the network connectivity and generate the number of friendships of each node. The interests were described using a Uniform distribution, from the following: travelling, sports, music, movies, tv-shows, books, magazines, games and art. As shown in the interest maps in Figure 2, most preferences are spread on large areas.

Vehicles generate messages constantly at a 2880-second interval, as the average number of messages sent by a person per day is approximately 30. The message topics are chosen randomly from node's interests, and the location of a message is set to the most frequented area of that node. Inspired by our previous results, we assumed that both context attributes are equally important in the decision making, thus they count with 0.5 weight for the overall context similarity [4].

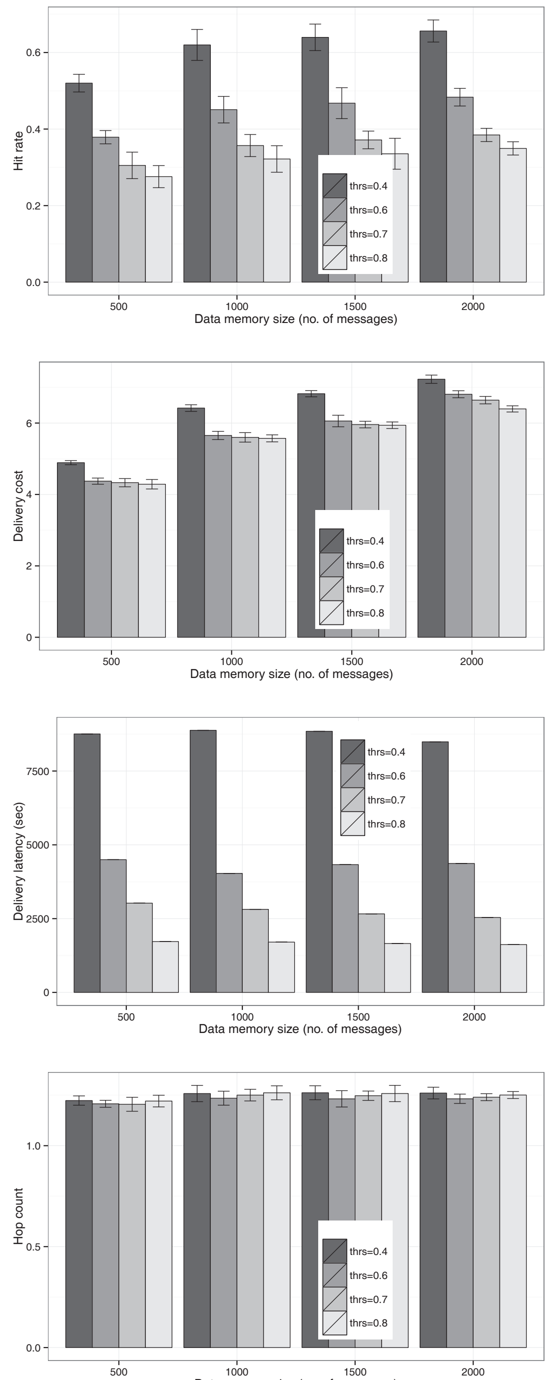

Figure 3. Simulation results for Vehicular ONSIDE.

$thr_{friends}$ was set to 0.5, since nodes are not strongly socially connected. As shown in [4], this value would not lead to network congestion. $thr_{encounters}$ was set of 0.3, a relatively lower threshold, since otherwise there would be too many message exchanges.

We first started our experiments using a similarity threshold set to 0.8 (dissemination in this case is greatly restricted). The experimental results are shown in Figure 3. In this case, for a message to be exchanged, besides the match of interests, the node should have visited the close surroundings of the message location quite often. The achieved hit rate, as seen in Figure 3, varies between 0.2 and 0.4 with the increase of the cache size.

To facilitate the understanding of the effect of the mobility history on dissemination, we experimented with varying similarity threshold values. A 0.6 threshold requires a node to have the interest matching the message topic, and to have visited quite frequently areas in the proximity of the declared message location. The 0.4 threshold restricts the exchange only to nodes that fulfil either the preference or the location requirement. A 0.5 threshold leads to requirements similar to the 0.4 case, but the probability of a node to have visited the defined message location, in this case, has to be equal to 1. Therefore, the *Vehicular ONSIDE* with a 0.5 threshold is almost similar to the basic ONSIDE dissemination strategy [4]. *Vehicular ONSIDE* with 0.0 similarity threshold is equivalent to the epidemic dissemination (disseminate all message to all encountered nodes). We previously shown in [4] that ONSIDE is able to reduce congestion and improve hit rate and delivery latency, when compared to solutions such as Epidemic or other advanced dissemination scheme (such as ML-SOR [15]).

As the similarity threshold decreases, the dissemination constraints are lowered and more message exchanges take place, thus increasing the hit rate and delivery cost (see Figure 3). Intuitively, the delivery latency should decrease, as more vehicles carry the messages and the probability of encountering nodes that are interested in the stored data increases. However, as more exchanges occur, the cache maximum capacity is reached faster and messages that would have been quickly delivered are replaced. With the increase of the data memory size, messages are replaced at lower rates and the latency decreases (see Figure 3).

The trace proved to be quite sparse. The time interval between encounters is large, therefore at every encounter a large number of messages has to be transferred. Older messages, some that were not yet disseminated, end up being replaced, thus lowering the hit rate.

V. Conclusion

Vehicular OppNets require interest- and location-centric messages to be disseminated. Therefore, an algorithm that leverages the location alongside other contextual information is needed. The proposed scheme, *Vehicular ONSIDE*, extends the basic ONSIDE strategy to allow the use of a multitude of context attributes, such as interests and location.

Vehicular ONSIDE uses Context Spaces modelling. While nodes retain their current context state, messages are associated with a situation space. The basic interest comparison, that was used in the base strategy, is replaced with a more complex similarity check operation that allows the use of different weights for each attribute. Therefore, the dissemination of messages can be controlled to a greater degree.

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