Context-aware Optimized Information Dissemination in Large Scale Vehicular Networks

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ABSTRACT
Context-aware inter-vehicular communication is considered to be vital for inducing intelligence through the use of embedded computing devices inside vehicles. Vehicles in a scalable environment may disseminate information about certain road traffic conditions, traffic incidents, free parking space or other relevant information to the neighboring vehicles in the vicinity. In this paper, we optimize the dissemination of such context information by predicting traffic patterns in a geographical region, including traffic hotspots. We optimized the relevance backpropagation algorithm with prediction capabilities to efficiently disseminate information. We evaluate our approach with the OMNET++ network simulator using realistic large scale data sets. Our experimental results show that by optimizing information dissemination we significantly improve the Network Traffic, availability and relevant information delivery in a large scale vehicular network.

Categories and Subject Descriptors
H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *information filtering, selection process.* H.3.5 [**Information Storage and Retrieval**]: Online Information Services – *data sharing.*

General Terms
Performance, Design, Experimentation.

Keywords
Context-Awareness, Predictions, Scalability, Optimization, Inter-vehicular.

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1. INTRODUCTION
Intelligent telematic application development is a research area that has gained a lot of attention from the research community. Application areas include emergency message transmission, collision avoidance, congestion monitoring and intelligent parking space location. According to the European Transport Whitepaper [15] in the year 2000 around 40,000 people lost their lives in the EU by road traffic accidents and 1.7 million were injured costing around EUR 160 billion. The cause of such incidents is mostly directly related to human error with a very small number of technical or system failures. Such issues can be handled by making intelligent use of information provided by the embedded electronic devices inside vehicles such as GPS or PDAs which will assist drivers but also by the information provided by other vehicles or stationary beacons next to the roads. As a result a critical aspect in the development of such intelligent applications is getting the right information at the right time and place.

"Context" is any relevant information that can be used to characterize the situation of entities where an entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves [1]. A system is *context-aware* if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task [1]. Context-aware dynamic settings in intelligent transportation and traffic management systems employ sensor network technologies to create new opportunities for co-operation and exchange of context information between nodes. Traditionally, ad hoc networks have been commonly used as a communication medium between mobile devices and/or a server at the backend [7]. In order to establish intelligent transportation using the relevant context information flow between vehicles and other static nodes like a parking meter, traffic light or any other road sign we need context-aware communication.

Scalability has often been a vital but a complex facet to address. In terms of context-aware communication *scalability* can refer, but is not limited, to the following properties; (1) Large number of participants e.g. 100,000 vehicles in a metropolitan city like Brussels, London or Amsterdam, (2) Large number of interactions in terms of message passing between the participants e.g. mobile social networking information exchanged between 50,000 passengers at an international airport, (3) Large area of interaction e.g. playing geo-caching within a country or a continent and (4) Long time span e.g. maintaining context information about 10,000 vehicles inside a smaller city over a time span of one year to predict traffic congestions on a road. For vehicular networks, in particular, we refer to it by covering the first two properties of the large number of vehicles and the large number of messages being passed as shown in Figure 1.

Nodes in a vehicular network move rapidly while the sensor nodes are static making it inappropriate to have a comparison with the algorithms used in the sensor network domain. Current peer-to-peer communication protocols like Gossip, Pastry and Chord [8] are inappropriate for context-aware information dissemination in a large scale network as the relevancy of information and routing patterns cannot be determined at the intermediate nodes. Dynamic routing of context messages supposes that at each node a decision is made about the most suitable candidate to forward the message to using the relevance of context into account. As a consequence, prediction of the direction likely taken by neighboring nodes is necessary for optimizing Network Traffic usage and for improving the relevancy of delivered context information. In this paper, we propose the use of Markov chains to predict overall traffic patterns in a large metropolitan area. It also allows us to identify traffic hotspots in that region. We optimized the relevance backpropagation algorithm with prediction capabilities to efficiently disseminate information. We evaluate our approach with the OMNET++ network simulator using realistic large scale data sets and measure various quality of service parameters in vehicular networks for different traffic scenarios and versatile telematic application requirements.

We will describe our motivating scenario with a set of requirements for optimizing information dissemination in section 2. We explain our improved relevance backpropagation algorithm with details about our prediction mechanism in section 3. Moreover in section 4, we provide insight on our simulated experimentation and results. In section 5 we discuss some of the related work. We end this paper with our conclusions and research ideas about future work in section 6.

2. MOTIVATING SCENARIO

In this section we describe a motivating scenario related to the health care domain. We also describe a basic set of key requirements for optimizing information dissemination.

2.1 Health care scenario

Efficient deployment of emergency response teams to a road traffic incident has always been a critical point. Traditionally, in case of an incident cellular or wired telephone networks are used to communicate the information about the location and time to the authorities. The problem with this system is that either the authorities are informed too late or the information is not sent to the closest emergency response teams. Let us consider a scenario where an older lady falls on the side walk of a road during the day time in the centre of Brussels due to some illness. The older lady presses the red button of the smart device she was provided with by the hospital in case of a medical emergency. The device sends out a help message by intelligently selecting the free internet enabled WiFi network available in the vicinity connected. The message instantly arrives at the nearest hospital's emergency response division and an ambulance is send to the site of the incident. The ambulance predicts traffic congestion near the site of the incident being the busy hour of the day. It sends emergency messages using its embedded wireless network to all the cars only moving or planning to go towards the site of incident to avoid possible road traffic congestions being the busy of hour of the day.

In this scenario the 'scalability' is mainly in terms of number of participants and the messages passed between them. The types of interactions involved in this scenario can be either in the form of a query or a message, for example;

- What is the location of the incident?
- Which response team is the nearest?
- Which network is suitable to send information?
- Send emergency signal to all vehicles travelling towards the incident.

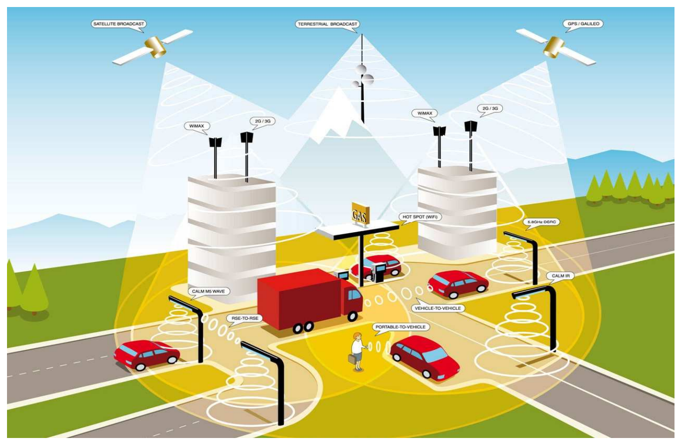

Figure 1: City-wide context-aware interactions [9].

All the vehicles involved will communicate in an ad hoc manner covering a large area.

2.2 Requirements for optimizing information dissemination

In order to optimize context-aware information dissemination we have to identify a set of requirements supporting such communication. We will briefly summarize the basic requirements [10] for large scale vehicular networks below:

R1: Location and direction-aware delivery of messages

It is always desirable to know the exact location of an incident for context-aware applications e.g. in the scenario 2.1 in case of an incident on the road the authorities should be notified about the exact location to react fast. Similarly, a context-aware application should be able to sense, manipulate and disseminate context information about direction and velocity of vehicles in the network to predict certain situations like traffic congestions or traffic accidents in specific regions. Moreover, to optimize the routing and delivery of a message, location-specific traffic (direction) patterns have to be taken into account. These patterns allow predicting the likely movement of the traffic flow in a specific area and depending on the time of the day.

R2: Temporal relevance

Temporal relevance is the desired behavior of a context-aware application dealing with routing efficiency. In a context-aware application on time arrival of information has always been a challenge using an efficient route. For example, if a road maintenance work is underway on 20th Apr 2009 between 10am and 5pm at Naamsestraat, Brusselsstraat and Lei in Leuven city, the information about traffic congestion or road condition is only valid on this specific date and time.

It is required that only the relevant context information arrives at a particular node on the right time and place. Temporal relevance involves efficient filtering of irrelevant information at intermediate nodes for optimal routing and faster delivery of context information. Again, prediction techniques enable the optimization of the message routing.

It is desirable to test and analyze these requirements so this imposes a new requirement for our simulated framework in a large scale vehicular network.

R3: Analyze Filtering, communication overhead and delivery efficiency

It is quite important to be able to quantify how much data that is being transmitted over the network is actually used by network peers both in total and on average for any given communication protocol scheme on an application basis. This quantification will guide the researchers to properly analyze, improve and compare various algorithms and protocols based on the parameters like Filtering, communication overhead and routing efficiency. In this paper, we compare our improved prediction enabled relevance backpropagation algorithm with the simple relevance backpropagation and with broadcasting technique.

3. TOWARDS INTELLIGENT INTER-VEHICULAR COMMUNICATION

In this section, we will describe our relevance backpropagation algorithm and its improvements with prediction capabilities. We later also discuss our methods for predicting traffic patterns for improving the information dissemination in large scale vehicular networks.

3.1 Relevance backpropagation

Our *Relevance backpropagation* algorithm relies on feedback of neighboring nodes to reduce the number of peers to forward the information to. The information is initially forwarded to the adjacent nodes unless maximum number of hops is reached. Each forwarding node reduces the hop counter, adds its identification and marks the message relevancy tag if the information is relevant for its purpose. The feedback technique is based on context information like position, velocity, direction, time-to-live, interest etc that decides whether the data that was received is relevant or not and also helps determine the information relevancy on the intermediate nodes. The feedback to the delivering node is initiated if the context information is *relevant, irrelevant*, *unused* or *duplicate information* is received reducing the information dissemination only to the interested nodes. A vehicular network is highly dynamic in nature and application dependent. As the context information can be provided by the application itself the routing of the information is adapted accordingly and perhaps different for various applications. So the network re-calibrates itself if a new node sends an *arrival beacon* or *an old node no longer transmits the feedback information*. In this mechanism the goal is to efficiently filter and route the relevant information as close to the source as possible in a dynamic network.

Algorithm 1. Relevance Backpropagation (input: fromPeer, contextMessage)

```
(messageRelevant, messageUnused, messageForwarded) = (false, false, false)
while (BeaconNewNode)
if (InFilterReceived(contextMessage.ID)) then
   BackpropagateMessage(fromPeer, DUPLICATE, contextMessage.ID)
else
   AddFilterReceived(fromPeer, context.Message.ID)
if (InFilterRelevant(contextMessage)) then
   messageRelevant = true
   BackpropagateMessage(fromPeer, RELEVANT, contextMessage.ID)
   if (InFilterUnsed(contextMessage)) then
   messageUnused = true
   LabelMessage(contextMessage, UNUSED)
else
   LabelMessage(contextMessage, IRRELEVANT)
if (contextMessage.hopsLeft > 0) then
  contextMessage.hopsLeft = contextMessage.hopsLeft – 1
  for each Peer p in ForwardFilter (adjacentPeers, contextMessage.ID) do
     messageForwarded = true
     ForwardMessage (p, contextMessage)
if (not messageForwarded) then
  if (not messageRelevant) then
     BackpropagateMessage(fromPeer, IRRELEVANT, contextMessage.ID)
  else if (messageUnused) then
       BackpropagateMessage(fromPeer, UNUSED, contextMessage.ID)
end while
RecalibrateNetwork( )
```

This algorithm is a best-effort algorithm which adapts itself according to the network configuration. The algorithm becomes intelligent with feedback information propagated in the network and by learning to efficiently predict patterns in a large scale vehicular network.

3.2 Prediction of traffic patterns

To predict the future movement directions of cars and thus optimize network traffic, we use Markov chains. A Markov chain describes at successive times the states of a system. Changes of state are called transitions. In our case, the states of the Markov chain correspond to locations on the map. The transitions represent probabilities of going from one location to another. The series of states of the system has the Markov property. A series with the Markov property is such that the probability of reaching a state in the future, given the current and past states, is the same probability as that given only the current state. So past states give no information about future states. If the machine is in state x at time n, the probability that it moves to state y at time n + 1, depends only on the current state x and not on past states. The transition probability distribution can be represented as a matrix P, called a transition matrix, with the (i, j)th element of P equal to $P_{ij} = P_r(X_{n+1} = j \mid X_n = i)$. The initial probability $P_r(X_{n+1} = j \mid X_n = i)$ is 1/m where m is the number of places that can be reached from the current place i. $Pr(X_{n+1} = j \mid X_n = i)$ could be updated by counting how often location j is reached from location i and dividing this number by the total amount of locations that were reached from location i. This means however that the past is as important as the present. In most environments the path the user usually takes while doing an activity will evolve through time. Consequently, the transition probability function should be updated in a way that recent transitions have more importance than those from the past. For that, the following exponential smoothing method can be used so that the past is weighted with exponentially decreasing weights:

P_{ij} = alpha * x_j + (1 - alpha)P'_{ij}

P'_{ij} represents the old probability and x_j is the value for the choice taken at location i with respect to location j. x_j is zero or one. If x_j = 1 then location j was chosen after i, x_j = 0 if not. Using this method, the sum of all outgoing probabilities remains 1, as it is required for a transition probability matrix. The parameter alpha is a real number between 0 and 1 that controls how important recent observations are compared to history. If alpha is high, the present is far more important than history. In this setting, the system will adapt quickly to the behavior of the user. This can be necessary in a rapidly changing environment or when the system is deployed and starts to learn. In a rather static environment, alpha can be set low.

3.3 Optimizing information dissemination with prediction capabilities

In order to optimize the information dissemination we have extended our earlier work [10] on the relevance backpropagation algorithm as discussed in section 3.1 with prediction capability by integrating the requirements mentioned in section 2.2. The algorithm initially learns the traffic pattern for providing input to the relevance backpropagation algorithm in the later stages. In the improved relevance backpropagation algorithm with prediction capabilities each node forwards the information to its immediate neighbors based on their highest probabilities to reach the destination.

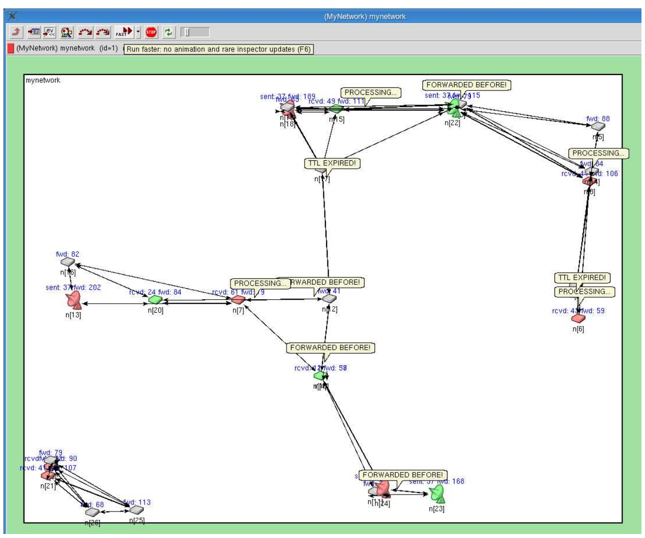

Figure 2: Experimental test-bed over OMNET++ to simulate vehicular networks.

For example, if it is predicted that a high percentage of neighbors will go in the destination direction, then the information is forwarded to only half of the nodes. On the other hand, if there are a low percentage of neighbors going in the destination direction, then the information is forwarded to all nodes.

The information flow patterns (probabilities) learned during the training / initial phase also help in determining information relevancy by identifying possible nodes which are moving towards the destination. This also limits unnecessary communication overhead between nodes in terms of messages passed.

4. EXPERIMENTATION AND RESULTS

In this section we will discuss our simulated experimentations and the results obtained. We use OMNET++ ver. 4.0, a real time discrete event-based network simulator, to test our improved relevance backpropagation algorithm with prediction capability over a large scale vehicular network using realistic dataset.

We have used a realistic dataset discussed later in section 4.1 and simulated for 100 cars. The parameters we have taken into account are for each node to perform simulated experiments;

(i) Time
(ii) Velocity
(iii) Direction
(iv) x and y coordinates
(v) Number of sent packets
(vi) Number of received packets
(vii) Number of forwarded packets
(viii) Time-to-live (TTL)

In our experiments, we let nodes move around like cars and let connections appear and disappear according to the range to other nodes. Some nodes acted as context providers whereas other nodes acted as context receivers. All nodes forward the information to their peers as long as the maximum TTL has not been reached and all context constraints are met. Figures 2 and 4 illustrate the visualization of the experiment with 100 nodes. There are green, red and gray nodes in the network where the color depicts the information interest. The antennas are information producers whereas the other nodes are information consumers. We carried out 4 experiments with (a) our improved relevance backpropagation mechanism with prediction capability (with 20%, 50% and 100% learning), (b) only relevance backpropagation and (c) plain broadcasting for a period of 24 hours each. The results for these experiments are explained later in more detail.

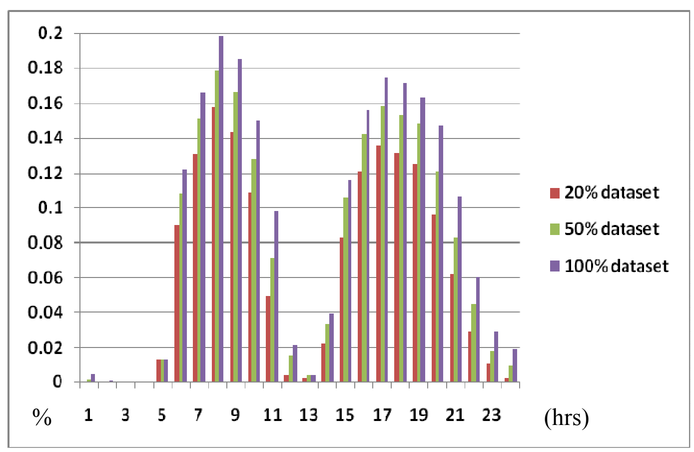

Figure 3: Coverage percentages per hour.

4.1Traffic pattern learning

The dataset used for evaluation is a set of traces from the multi-agent microscopic traffic simulator (MMTS)[1] developed by K. Nagel. It is capable of simulating traffic over real regional road

[1] http://www.lst.inf.ethz.ch/research/ad-hoc/car-traces/

maps of Switzerland with a high level of realism. The behavior of people is modeled and their movement with vehicles is reproduced for a period of 24 hours. Individuals in the simulation are distributed over cities and villages in an area of 250 km X 260 km. All individuals choose a time to travel and a route according to where they live and current road congestion. The complete dataset contains 260,000 vehicles with in total more than 25,000,000 recorded direction and speed changes.

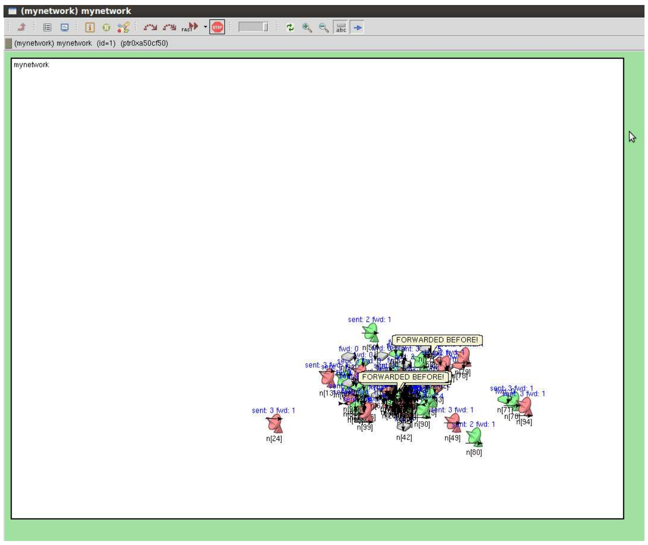

Figure 4: Experimental test-bed over OMNET++ to simulate vehicular networks.

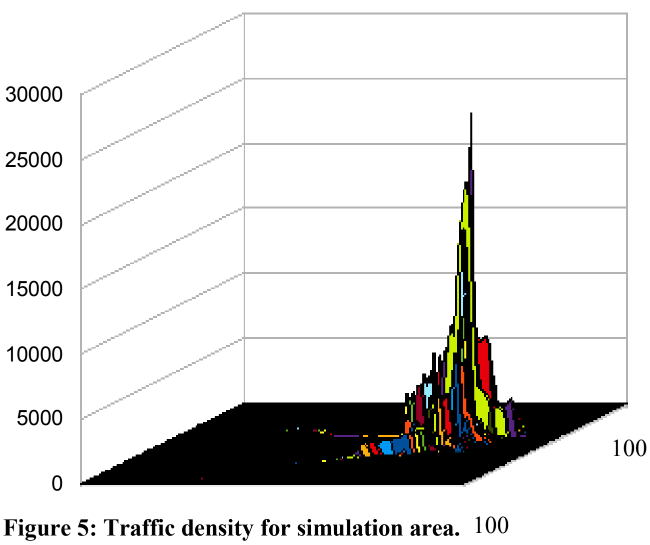

Figure 5: Traffic density for simulation area.

As a preprocessing step, movement traces were grouped per vehicle and coordinates were normalized to a value between 0 and 1. As traffic movement patterns are different according to the time of day (e.g. a net inflow of cars into cities in the morning, and outflow in the evening), each hour of the day was modeled by a different first order Markov chain, giving 24 Markov chains. Note that the use of higher order Markov chains is not suited here, since the goal is to obtain the overall probability of going in a specific direction given the location, irrespective of the cars being at another location before.

The area was subdivided into a 100 x 100 grid, making a total of 10,000 locations, corresponding to the states of the Markov chains. Probabilities of going from one location to another were learned with alpha equal to 0.05 and 0.08, based on 20%, 50% and 100% of the dataset. Since going from one location to another is (per time step) only possible to neighboring locations, the transition probability matrix dimensions were reduced from 10,000 X 10,000 to 10,000 X 8.

Figure 3 shows the coverage percentages for each hour of the day. A location in the simulation area is covered if at least one vehicle visited it. E.g. at 8 am, in 20% of the locations of the grid there was traffic going on when looking at the whole dataset, while there was traffic in 16% of the locations when taking a random 20% of the dataset. It is clear that rush hours are from 8 to 10 am and from 16 to 20 pm. As can be seen from the figure, there is no significant difference in coverage when taking into account 20%, 50% or 100% of the dataset. It follows that a part of the dataset is representative for the whole, and generalization of the learned probabilities is possible.

In the MMTS dataset, there are big differences in traffic density depending on the location (Figure 5). In the south-east part of the simulation area, there is a major city where traffic density is very high. The X and Y axis of the graph denote longitude and latitude of the area. The vertical axis shows the absolute numbers of cars passing by at a location during one hour.

The decision to forward messages to other cars in the neighborhood will therefore not only depend on the transition probability matrices but also on the densities of the surrounding locations.

4.2 Simulated experimental results

In the experiment using the flooding mechanism the context information was broadcasted in the network to every node. In our experiments with both the (improved and simple) relevance backpropagation algorithms only relevant context information was sent out to the interested nodes in the network.

There are several types of messages in our simulation like (i) sent (M_s), (ii) unique received (M_{ur}), (iii) unique sent (M_{us}) (iv) forwarded (M_f), (v) duplicate (M_d) and (vi) dropped (M_{drop}). We measured the following parameters during our simulated experimentation and present results in Figure 6.

- *Network Traffic (NT)*

$$NT = \sum_n (M_s + M_f)$$

  There is a significant difference in Network Traffic utilization for our improved backpropagation mechanism with predictions capability up to 95% as shown in Figure 6. A lower network traffic is considered to be better.

- *Relevancy (R)*

$$R = \sum_n ((M_{ur} + M_d) - M_{drop}) / \sum_n (M_{ur} + M_d)$$

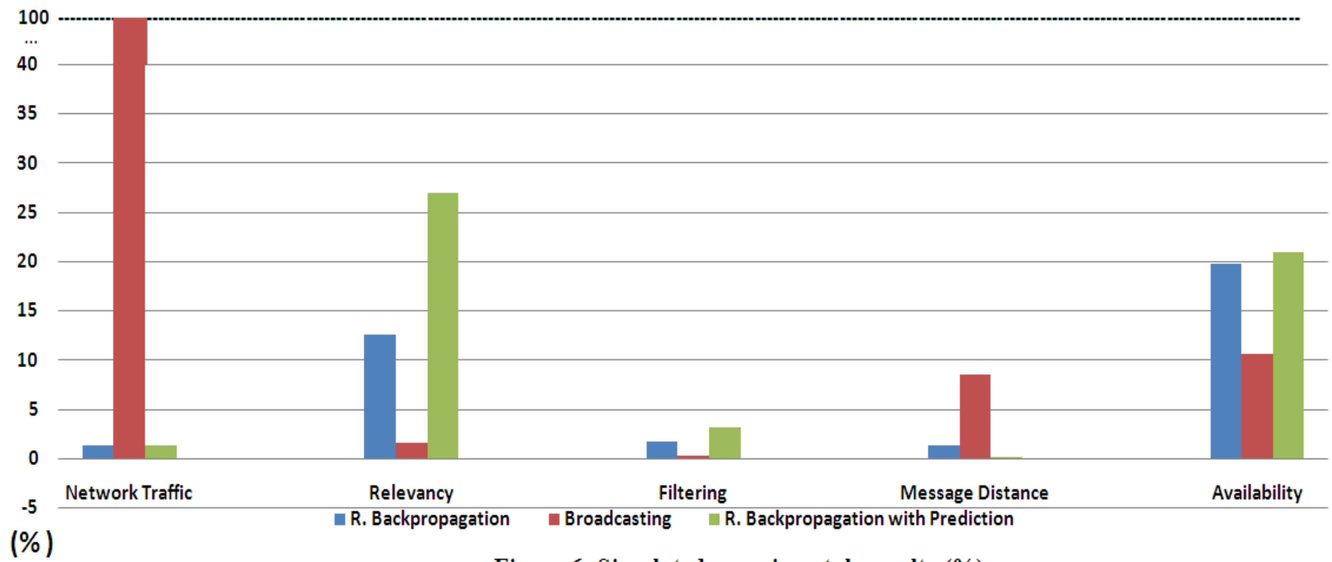

Figure 6: Simulated experimental results (%).

There is also a significant difference of about 35% higher in our improved relevance backpropagation mechanism with predictions capability compared to plain broadcasting. It illustrates that nodes get more relevant information (i.e. the nodes receive less information they are not interested in) as shown in Figure 6. A higher relevancy ratio is considered to be better.

- *Filtering (T)*

  $$F = (1 - (M_f / \sum_n (M_{ur} + M_d)))$$

  The 15% filtering rate for our improved backpropagation mechanism with predictions capability compared to the plain flooding can be explained by the fact that messages are only routed where they are relevant, in some cases broadcasting may deliver messages that our approach does not. However our improved algorithm is still slightly better than the simple relevance backpropagation algorithm as shown in Figure 6. The higher the filtering the better it is in a network.

- *Message Distance (MD)*

  $$MD = \sum_t \text{Edges} / \sum_t \text{Nodes}$$

  In our improved relevance backpropagation with prediction capability the message distance of the information is slightly higher than in plain broadcasting (10%) and simple relevance backpropagation algorithm (8%) as shown in Figure 6. A lower message distance is better in a network.

- *Availability (A)*

  $$A = \sum_n M_{us} / \sum_n M_{ur}$$

  The availability of the context information is about 2% higher in the simulation results when using our improved and simple relevance backpropagation mechanism then when using plain flooding as shown in Figure 6. A higher availability ratio is better in a network.

Reduced network traffic is an achievement in the area of network communications. One might argue that in the current modern era of technology and communication the world has enough bandwidth available for use. But with the growing demand for high speed communication this resource which we enjoy today will be scarce in the near future.

5. RELATED WORK

In [6], Nadeem et al. present a formal model of data dissemination in Vehicle Ad-Hoc networks (VANETs). They measure how the performance of data dissemination is affected by bi-directional lane mobility. Three models of data dissemination are explained and simple broadcasting technique is found to be sufficiently enough in their simulated experiments. In our research, we deal with the optimized directional dissemination of context information with predictions.

Mahajan et al. present an idea about the WiFi-based connectivity and communication between base stations and moving vehicles in [5]. Vehicles mobility cause gray periods of poor connectivity which according to the authors are caused by variability in the urban radio environment combined with the vehicle traversing areas of poor coverage. We envision that for large scale vehicle network the use of simple WiFi based communication will be impractical.

In [4], Eichler et al. address the issue of optimal information dissemination in vehicular networks. The authors proposed a framework which integrates many of the existing broadcast based strategies that deal with the reduction of the superfluous transmissions. Our approach uses the idea of disseminating the optimized relevant context information using the prediction of the future state of a node in the network.

The use of a propagation function for retrieving targeting areas and preferred routes for information delivery has been addressed in [2]. Costa et al. integrate the propagation function with several probabilistic routing protocols with some performance overhead. In our research, relevance backpropagation algorithm with prediction capabilities handles the dynamic nature of a mobile network without creating a communication overhead.

A comparative performance comparison between three data dissemination protocols (i) Directed Diffusion, (ii) Two-Tier Data Dissemination and (iii) Gradient Broadcast for wireless sensor networks is discussed by the authors [3]. In our research, we found that two-tier dissemination and gradient broadcasting over a large scale network are not cost efficient in terms of implementation complexity and processing overhead. So we make use of a combination of directional diffusion and gradient broadcast of context information in a better manner by predicting the area of spatial coverage and information relevance feedback acting as a cost function in gradient broadcast so that the context information can only be directed to a specific region with minimal cost and effort.

Markov chains and hidden Markov models are used in a wide range of applications. In the domains of speech recognition and the prediction of genome sequences in bioinformatics they have proven to be a fruitful approach. Recently, hidden Markov models have been used to learn movement patterns in a mobile network to perform GSM tracking [11]. Information related to the paths followed by mobile phones can be learned using hidden Markov models and the prediction method allows for the anticipation of resource allocation. This means dynamic scheduling takes place. Chinchilla et al. [12] use Markov chains to predict to which access point a wireless client will connect, given the last access point the client was connected to. The goal is to improve the performance of the wireless infrastructures by load balancing, admission control and resource reservation across access points. Mobility patterns of clients are learned using historical information. The system has been tested on a university campus with a wireless infrastructure and the next access point a wireless client connects to can be predicted with high accuracy according to experimental results. Papadopouli et al. [13] present a methodology that shows how mobility patterns and associations between users and access points evolve not only in space, but also in time. Therefore wireless access patterns are characterized based on stochastic parameters such as visit duration. Chakrabortyet al. [14] evaluate several heuristics that, based on the movement history of a mobile client, estimate an optimal time for communication. Time is optimal when the least energy will be used. The goal is thus to minimize the energy consumption necessary for wireless communication. Statistical information about a client's movement history is represented as heuristics based on Markov models.

6. CONCLUSION AND FUTURE WORK

Vehicles in a scalable environment may disseminate information about certain road traffic conditions, traffic incidents, free parking space or other relevant information to the neighboring vehicles in the vicinity. In this paper, we optimize the dissemination of such context information by predicting traffic patterns in a certain geographical area. It also allows us to identify traffic hotspots in that region. We optimized the relevance backpropagation algorithm with prediction capabilities to efficiently disseminate information. We evaluate our approach with the OMNET++ network simulator using realistic large scale data sets and measure various quality of service parameters in vehicular networks for different traffic scenarios and versatile telematic application requirements.

The simulation results show that by using our optimized relevance backpropagation mechanism significant improvement is realized in terms of Message distance and relevancy of context information to 8% and 35% respectively in comparison to the simple relevance backpropagation. Moreover, other parameters like Network Traffic and availability are also slightly better than the simple relevance backpropagation algorithm.

We plan to investigate the network and context properties to get a broader view of the communication mechanisms used earlier for our simulated experiments.

In the future we also plan to investigate the same network parameters by inter-connecting a real embedded smart device like a PDA, GPS or an embedded vehicular computer with the simulation environment to analyze the behavior of the real smart devices. Later on this will enable us to see how our relevance backpropagation mechanism can be improved over other large scale networks with real applications.

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