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HISTORY BASED ROUTING FOR RESCUE OPERATIONS IN VEHICULAR SENSOR NETWORKS

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Abstract—In vehicular sensor networks (VSNs), an increase inthe density of the vehicles on road and route jamming in the network causes delay in receiving the emergency alerts, which results in overall system performance degradation. In order to address this issue in VSNs deployed in dense urban regions, in this paper, we propose collaborative learning automata-based routing algorithm for sending information to the intended destination with minimum delay and maximum throughput. The learning automata (LA) stationed at the nearest access points (APs) in the network learn from their past experience and make routing decisions quickly. The proposed strategy consists of dividing the whole region into different clusters, based on which an optimized path is selected using collaborative LA having input parameters as vehicle density, distance from the nearest service unit, and delay. A theoretical expression for density estimation is derived, which is used for the selection of the "best" path by LA. The performance of the proposed scheme is evaluated with respect to metrics such as packet delivery delay (network delay), packet delivery ratio with varying node (vehicle) speed, density of vehicle.

Index Terms—Congestion control, learning automata (LA), performance evaluation, routing, vehicular sensor networks (VSN).

1 INTRODUCTION

An increasing number of current generation vehicles are equipped with advanced wireless technologies to access the network resources on-the-fly and improve the safety of the persons who are riding such vehicles [1]–[4]. These advanced technologies provide vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication infrastructure for a secure and comfortable journey. The passengers in the vehicles have information about the external environment with respect to parameters such as the density of traffic, the distance of the lights from the current position, the map of the sites to be visited, the quantity of pollution outside the car, and other environment parameters [5], [6]. Vehicles share the information with one another, so that rescue operations can be initiated at once in a particular community, if required. However, due to continuously changing topology with the speed of the vehicles, designing a collaborative routing strategy for vehicular communication is a challenging task [6]. Recently, proposed systems such as FleetNet [7] have investigated the data dissemination and mobility support for efficient communication with discovery of various types of services. FleetNet uses an IPv6-based addressing scheme to connect all the vehicles to the Internet using gateways alongside the road. Some research works [8], [9] in this direction have used the density information on roads to select the optimized routes, but due to the high mobility in the network, sometimes decisions based on statistical data can cause routes to be incorrectly computed. More recently, Yang et al. [4] proposed a scheme, in which the selection of a particular route is decided based upon the transmission quality and the density of the network. The selection of the particular route is done in an optimized manner by selecting the density and duration of the traffic lights. Most of the earlier solutions (e.g., [10] and [11]) may work well for low density areas, but with an increase in the density of the region under investigation, particularly in dense urban regions, it would be a challenging problem to route the packets due to the congestion in the network [12]–[14]. Hence, there is a requirement of an optimized solution, which is adaptive with respect to the topological changes due to the high velocity of the vehicles and generated alerts at constant intervals.

Keeping in view the aforementioned challenges and drawbacks in the existing works, we propose a collaborative LA-based routing strategy that can help the community of people to use the rescue operations. In the proposed approach, an automaton learns from its environment and learns the parameters such as vehicle density and distance from road side units (RSUs). Treating these parameters as input variables, the automaton produces an output. The values of these parameters are passed on to the neighboring vehicles in a collaborative manner. The selection of a route depends upon the output produced by the LA by taking into the consideration the vehicle density, and distance from the destination in that region.

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2 Related Works

In order to appreciate the contributions of this work, let us review some of the relevant pieces of literature. LeBrunet al. [15] proposed a motion vector routing algorithm (MOVE) to preserve the connectivity of the vehicle with an RSU. In this paper, the authors proposed the use of the neighboring vehicle velocity to predict the closeness of the traveling vehicle with the others. Zhao and Cao [16] proposed a vehicle-assisted data delivery (VADD) protocol for vehicular ad hoc networks (VANETs). The authors proposed a new metric called the expected delivery delay metric to guide during the routing pro-cess. However, the proposed scheme has limited performance in situations where an adaptive decision needs to be taken based upon the input parameters such as the density of nodes and the distance. Fallahet al. [17] proposed a scheme for a vehicle safety system, in which they proposed an adjustment of rate and range parameters of the vehicles. The proposed scheme was evaluated in different network environments with respect to various evaluation parameters and its performance was found to be satisfactory in comparison to other existing schemes.

Lee et al. [18] proposed a middleware approach for urban monitoring using sensor nodes. The authors proposed an an-alytical model by taking various scenarios of mobility and stability of the sensor nodes. The performance of the proposed scheme was better than the other existing schemes. Rawatet al. [19] proposed an approach, in which power and size of the contention window were changed for service differentiation. In their approach, the authors compute the local density, and then, the transmission range is made adaptive using this parameter. Moezet al. [20] proposed an efficient routing protocol for dense urban regions. In their work, the distance from the final destination is first computed, and that value is used to find an optimized path in dense urban region. Jeonget al. [21] proposed a scheme, in which the vehicles on the road calculate their data delay to the access points (APs) in their regions, and then, this information is shared with the other vehicles.

Tatchikouet al. [22] proposed a collision avoidance scheme using VANETs. The authors proposed a collision avoid-ance scheme using an efficient packet forwarding mechanism. Buchenscheitet al. [23] proposed a warning system for rescue operations using VANETs. In the proposed scheme, the vehi-cles share the information about the best suitable path. Fiore and Barcelo-Ordinas [24] proposed a scheme for optimized AP deployment and for download of data from these APs. Zhou et al. [25] proposed a routing scheme for distributed media services for VANETs in a peer-to-peer manner. The authors proposed an optimization model for data transfer and cache update for user satisfaction. Burgess et al. [26] proposed a routing scheme for vehicle-based disruption-tolerant networks.

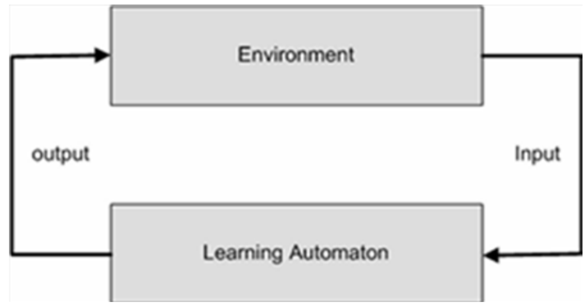

Fig. 1. LA. Automaton interaction with an

The proposed scheme was based on prioritization and schedul-ing of routing packets. Zhou et al. [27] proposed a cross-layer routing design for VANETs. The proposed scheme establishes end-to-end connectivity and semantics for various applications in VANETs. Leontiadis and Mascolo [28] proposed routing scheme by taking into consideration the mobility and location of the vehicles in VANETs. Zhang and Wolff [29] proposed a routing scheme for VANETs for use in those regions where fewer infrastructures exist for the vehicles to communicate with one another.

It has been found in literature that computational intelligence techniques can be useful to solve various complex engineering problems from diverse backgrounds [30]–[39]. All these prob-lems are solved by using the concepts of learning and inter-actions of objects with an environment that provides constant feedback to these objects such that these can take adaptive decisions. Learning can guide and improve the routing criteria in many adaptive systems [30]–[39].

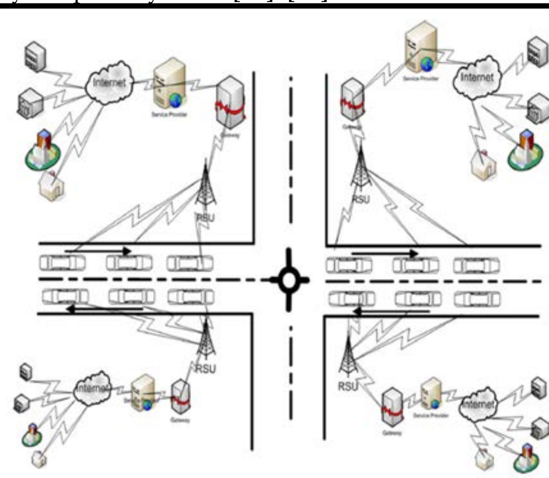

Fig. 2. System model in the proposed scheme.

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3 BACKGROUND AND PRELIMINARIES

Fig. 1 describes the working of LA. An automaton takes the input parameters as previously defined and acts according to these parameters to produce an output. It is an adaptive learning technique with decision-making machine having the capability of improvement by learning from its environment so that it can choose the optimal action from a finite set of allowed actions through repeated interactions [30]–[39]. The objective of a learning automaton is to find the optimal solution with minimized penalty received from the environment [30]–[39].

Mathematically, LA is defined as (Q, K, P, δ, ω), where Q = {q1, q2, . . . , qn} are the finite set of states of LA; K = {k1, k2, . . . , kn} are the finite set of actions performed by theLA; P = {p1, p2, . . . , pn} are the finite set of response received from the environment; and δ : Q×P→Q maps the current state and input from the environment to the next state of the automaton; and ω is a function that maps the current state and response from the environment to the state of the automaton [30]–[39].

4 SYSTEM MODEL AND PROBLEM FORMULATION

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Fig. 2 shows the system model in the proposed scheme. A VSN consists of n number of nodes with every node having a unique identity. It is assumed that every node is equipped with a Global Positioning System (GPS), digital map, wireless transmitter, video camera, and storing device. As shown in Fig. 2, there are different communities on each side of the road. These communities are connected to the Internet using a gateway via the service providers (SPs) in their vicinity. There are two types of communications considered in the proposed scheme: V2I and V2V. For V2I, one RSU/AP is deployed in different regions of the area to be investigated. The RSU sends/receives the information from gateway to SP to the community of peoples. For the V2V case, each vehicle communicates and shares the information with the other vehicle in peer-to-peer manner. A road is divided into clusters, which are aligned in a single row. Fig. 3 shows the relationship between velocity and density of the network. With an increase in the density of the network, the average velocity of the vehicle decreases due to traffic congestions and an increase in collision probability.

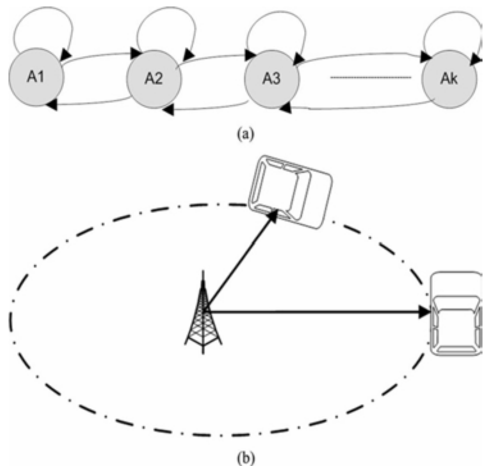

Fig. 3. (a)–(b). Route Selection with (a) collaborative information sharing and (b) density estimation in the proposed scheme.

Fig. 3(a) shows how the interaction between different states where automaton is working is done, while Fig. 3(b) shows how the distance from the RSU influences the route selection process.

4.1 Problem Statement

Let L = {L1,L2,...,Ln} be the current location set of the vehicles; θ = {d1,d2,...,dn}, the distance from the neighboring RSU; D = {k1,k2,...,kn} the vehicle density set; and R = {R1,R2,...,Rn} the current routes set. The current location of the vehicle can be found at any time by using GPS. To make a transition from one state to another, we consider a transition function as defined in the following: δij : x → R (1) where x =(L,θ,D) are input parameters, 1 ≤ i ≤ n,1 ≤ j ≤ n The right-hand side of (1) contains the possible routes and δij is a stochastic function, which acts according to the input parameters. It maps the current location of the vehicle, the distance from the RSU and the density of the vehicle to suitable route. The density of the vehicle is measured by the number of vehicles in a particular cluster/region to the total number of vehicles at any instant and is calculated by (1) as defined in the following:

$$D = \frac{\sum_{i=1}^{n} NV_i}{\sum_{i=1}^{n} n_i} \quad (1)$$

Where NVi is the number of vehicles in cluster i, and ni the total number of vehicles on the road. We have set a predefined threshold range of 250 m for computing the number of vehicles in a region.

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5 PROPOSED APPROACH

A packet containing the parameters (L,θ,D,δt) is transmitted to the intermediate node having information about the vehicle current position, distance from RSUs, vehicle density, and total delay incurred in a particular region. This phase is completed by the automaton and corresponding to each action taken by the automaton, it is penalized or rewarded by some constant value based upon which the automaton decides its next action. Two types of action are possible for the automaton as reward and penalty. In the reward function, if the current node is the destination, then cumulative weight is updated as aforementioned with ψ∈[0,1] as a reward constant. Otherwise, the transition function is used for update the cumulative weight as aforementioned. ξ is a constant to estimate how good is the path selected. A higher value of ψ indicates faster convergence toward the optimized path and lower value indicates slow convergence toward the optimized path. Similar to the reward function, a penalty is associated, as shown in the following. In the aforementioned, φ ∈ [0,1] is the penalty parameter, which decreases the cumulative weight for every unsuccessful transmission. The specific values of φ in this interval is taken to minimize the effect of

TABLE I

SIMULATION PARAMETERS

Parameters	Values
Number of Vehicles	500
Communication Range	250m
Simulation Area	$500 \times 500\ m^2$
Simulation time	200sec
MAC protocol	IEEE 802.11 p

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penalty for unsuccessful transmission. As for every unsuccessful transmission, action of automaton is penalized so we have taken values of φ as previously defined to minimize the penalty. Based on the aforementioned, every automaton at respective nodes selects or rejects a packet based upon values and updates its action probability vector as previously defined. If the newly arrived packet has higher distance and density than the packets, which has been received in the past, then the status of the current packet is declared to be rejected; otherwise, if the newly arrived packet has the same distance and density for the packets, which has been received in past by the intermediate node, then it is added in the path for the final destination and can be used in future. Furthermore, if the newly arrived packet has lower distance and density than the packets, which has been received in the past, then this packet is accepted by the automaton. In such a case, all the previously found paths are discarded and the newly found path is considered for inclusion in the final path. We have assumed the clustering of the nodes as described in [6], [9]. Wi(t) is the cumulative weight of these paths as follows: $Wi(t) = (1/N(np))\sum_{j=1}^{N(np)} W(j)$ where N(np) is the number of times weight along that path has been computed, and W(j) is the weight of an individual path.

Algorithm 1 Reward function

if (current_node = destination)

then Wi(t)=Wi(t)+ψ

elseδij = ξ×Wi(t) + (1−ξ)Wi(t)

end if

Algorithm 2 Penalty function

if (current_node = destination)

then

Wi(t)=Wi(t)×φ

else

Wi(t)=Wi(t)+ψ

δij = ξ×Wi(t) + (1−ξ)Wi(t)

end if

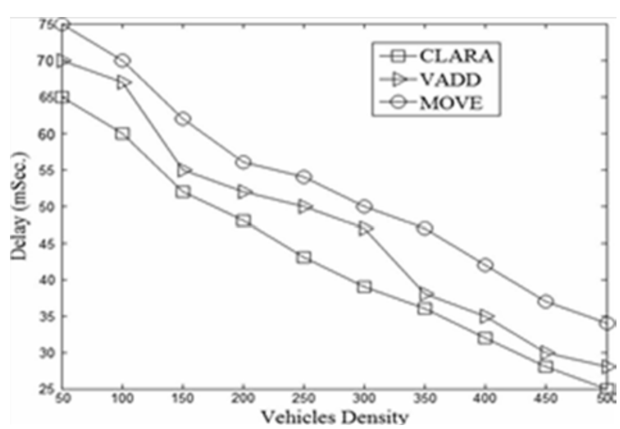

Fig. 1. Network delay with variation in density.

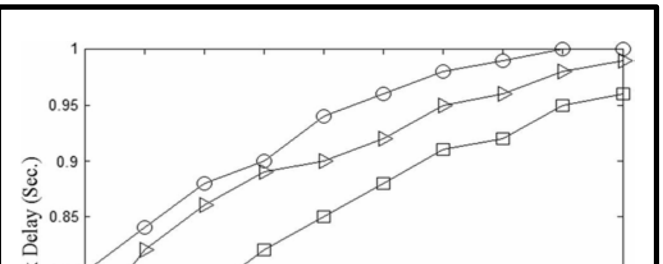

Fig. 2. Network delay with variation in vehicles
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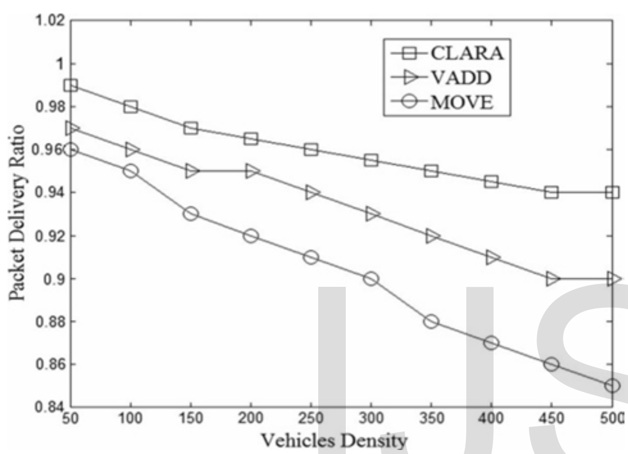

Fig. 3. Packet Delivery Ratio with variation in vehicle density

5.1 Simulation Environment

The proposed scheme was evaluated on NS2 and its performance was compared with the existing com-peting schemes: MOVE [15] and VADD [16]. Each vehicle's movement pattern was determined by a Hybrid Mobility model [43]. The packet generations from the vehicles were considered to be an exponential distribution with a mean of 10 s; packets were dynamically generated from 500 vehicles in the road network. The simulation parameters that were considered in the study are described in Table I.

5.2 Results and Discussion

5.3.1 Impact of Node Density on Network Delay:

Fig. 1 shows the impact of the node density on the network delay in the proposed scheme. As shown in the figure, with an increase in the number of nodes in the network, the network delay in the proposed scheme decreases compared with the benchmark schemes. This is due to the fact that the proposed scheme uses an LA-based approach, which intelligently adapts to the situations such as congestion/jamming quickly and takes the decision on its own, which results in a considerable decrease in the network delay compared with the other approaches in its category.

5.3.2 Impact of Node Density on Packet Delivery Ratio in the Proposed Scheme:

Fig. 2 shows the impact of the proposed scheme on the packet delivery ratio. The results show that the proposed scheme has a higher packet delivery ratio than the other two schemes with the same density level. As shown in the figure, the "gap" between the plots corresponding to the obtained packet delivery ratio in the proposed scheme and the other two schemes becomes wider. The reason for such behavior with the same level of density of nodes is due to the fact that the proposed scheme intelligently chooses the route (adaptively) from the available ones using an intelligent LA approach that learns with the passage of time. Thus, the decision taken by LA for the selection of best path in the proposed scheme is better than the other existing schemes reported in the literature. As a result of this, the packet delivery ratio in the proposed scheme increases considerably compared with the other approaches.

5.3.3 Impact of Node Speed on Network Delay in the Proposed Scheme:

Fig. 3 shows the impact of the proposed scheme on network delay with an increase in node speed. As shown in the figure, with an increase in the node speed, the network delay also increases. This is due to the fact that with an increase in the node speed, the distance between vehicles also increases and, consequently, it is difficult to maintain the connection between the nodes, thereby resulting in an increase in the network delay. However, connectivity is efficiently maintained in the proposed scheme with an increase in node speed due to the selection of adaptive paths intelligently using a LA-based approach.

6 CONCLUSION

In this paper, we have proposed a new collaborative LA-based routing scheme that can help in rescue operations for dense urban regions using VSNs. Each moving vehicle has an intelligent sensor deployed, which selects the route adaptively and intelligently, based on the density of the vehicle on the road, the distance from RSUs and delay incurred during transmission. Vehicles communicate with one another in a collaborative manner in order to share the information about these variables and intelligently select the best route to reach the final destination. LA selects the best path from the available ones. The performance of the proposed approach was evaluated along with the existing competing approaches with respect to performance metrics of packet delivery ratio and packet delivery delay by

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varying the node speed, the density of the vehicles. The results obtained show that the proposed scheme shows superior performance as it shows a reduction of 30% in the network delay and an increase of 20% in packet delivery ratio compared with the existing schemes that we considered in this study.

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