

A Multi-Modal Learning Assisted Vehicle Selection for Optimizing IoV Communications in Medical Information Handling

Tamizharasi Thirugnanam^{#1}, Muhammad Rukunuddin Ghalib^{#2}(Corresponding Author)

[#]School of Computer Science and Engineering,

Vellore Institute of Technology, Vellore, Tamil Nadu, India

¹tamil.thirugnanam@gmail.com, ²ghalib.it@gmail.com

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Abstract:

Internet of things (IoT) incorporated with intelligent transportation systems (ITS) aided the design and development of internet of vehicles (IoV) for real-time applications. The applications of IoV in healthcare and medical field include smart monitoring and emergency vehicle transportation for improving its efficiency and improving reliability. Data handling and communication management are complex tasks in IoV aided healthcare applications due to the conventional issues in vehicular communication. To address the problem of data stagnancy and intermittent transmission in IoV communication, a multi-modal tree-driven transmission (MTT) scheme is designed. This transmission scheme balance is between neighbor selection and medical data management by preferring adaptive tree for transmitting emergency messages. By exploiting the multi-modal characteristics of the vehicle and data, the transmission scheme is scaled in an end-to-end manner. Precise neighbor selection, independent decision-process are the intermediate solutions assimilated in MTT for improving successful latency less delivery of medical data from the smart vehicles. The performance of the proposed MTT is assessed through simulations and is verified using the metrics latency, storage handling, transmission backlogs and data processing rate.

Keywords: IoT, IoV, Healthcare Information Transmission, Multi-modal Attribute Classification, Tree Routing

I. Introduction

Internet of Vehicles (IoV) is a modern road-side internet/ cloud assisted communication paradigm constructed upon moving vehicles. Conservative intelligent transportation systems (ITS) and internet of things (IoT) standards are bonded for designing IoV. The application of IoV is extended in smart city environment, where a moving vehicle is responsible for providing self-configured traffic and communication management, real-

time application support, location tracking, driving safety, message exchange, etc. Communications is the fundamental block of designing IoV accomplished through interoperable technologies [1]. Vehicle assisted communication is designed using proprietary standards such as dedicated short range communication (DSRC), wireless access in vehicular environment (WAVE) and IEEE 802.11p with adaptability and flexibility. These standards facilitate both vehicle to vehicle

(V2V) and vehicle to infrastructure (V2I) communication depending on the application demand and user requirement. In addition to the communication facilities, intelligent behavior of the vehicles in decision-making, storage access and retrieval, event detection and response are granted by the external technologies such as IoT [2]. Smart communication technologies administered for mobile and cellular communications provides better scaling of the coverage area with respect to the velocity and direction of the vehicles. Therefore, the end-user/ consumer is granted with seamless communication support and road-side featured applications [3].

The development of smart city environment enriched the demand for intelligent vehicles for connecting consumers/ end-users with different digital data in transportation. The base IoT environment visualizes real-world entities in the form of digital things with communication ability. IoV is dependent on this attribute to ensure seamless support for information access and processing and communication. A variety of applications including healthcare exploit the features and technologies in monitoring and processing entity-related information [4]. In smart cities, smart vehicles are deployed for monitoring patient health and communicating the observed information to the health center for diagnosis. In this scenario, bio-medical sensing and monitoring devices are equipped in the vehicle that is connected to the on-board unit (OBU) of the vehicle for external communication [5]. Therefore, IoV in health care is a perfect example of heterogeneous real-time applications providing patient care and emergency health data dissemination. To ensure reliable health information sharing and data dissemination [6], the intelligent vehicle performs routing and transmission decisions of its own. The decisions of the vehicles are

assisted by distributed sources that are connected using common internet/ cloud [7].

Though IoV in healthcare provides seamless solutions for information exchange and data dissemination, the intrinsic attributes of the vehicles arise some linear issues in the communicating environment. Vehicle speed, acceleration, direction of movement, etc. are some of the intrinsic attributes that influence the performance of vehicular applications. In order to retain the performance of healthcare application, issues in data transmission and path selection is to be confined [6]. Time-constraint delivery, fewer backlogs and continuous health update are some of the vital requirements from the health center to which the vehicle is communicating. Besides, the collision factors, network dynamics, and traffic management are some of the other default challenges in vehicle-assisted network communications. To cope up with the demands of healthcare applications with reliable support, the decision making capability of the devices is to be improved by integrating computational level architectures and frameworks/ techniques [7]. Machine learning is a conceptual analysis functional genre that leverages the performance of the host paradigm [8]. Machine learning concepts are exported to vehicular networks for addressing and resolving the issues in routing and transmission, network dynamics management, resource exploitation, connection stability, etc. [9]. In this article, support vector machine (SVM) classifier is deployed for addressing path loops and data stagnancy in healthcare vehicle communication.

Related Works

Ding et al. [10] proposed a machine-to-machine driven framework for streamlining IoV transmission suppressing the issues due to network dynamics and traffic. The authors defined a novel data transmission scheme between the mobile terminal and vehicle with a wireless monitoring feature. Augmenting the

energy, received signal strength (RSS) and velocity features, energy efficiency and reliable transmission is achieved in the proposed framework.

Software defined Internet of Vehicles (IoV) architecture is designed by Abbas et al. [11] for leveraging the routing process with the awareness of network dynamics. This architecture operates control and data plane separately. The road-aware routing process assisted by SD-IoV facilitates segmented multi-hop communications between vehicles and infrastructure. In this architecture, the routing process employs a dedicated controller for reducing latency in the communication between cellular networks and vehicles.

Another proposal of Abbas et al. in [12] discusses infrastructure assisted road-aware routing (IARAR) protocol for enhancing vehicular communication. The route established in this protocol considers multiple routing metrics such as: velocity, vehicle density, communication range, hop count, and path endurance for selecting a new neighbor. More specifically, it consents vehicular velocity and path endurance for selecting stable neighbors achieving better delivery ratio, delay and overhead.

Thakur and Malekian [13] emphasized the significance of IoV in safety-driving applications and traffic management. IoV is driven by peer-to-peer, inter and intra vehicle communications by selecting suitable communication channel for supporting the fore-mentioned applications. The reliability of the IoV relies on communication technologies including ZigBee, Wi-Fi and DSRC standards.

A novel transmission mechanism for emergency data (TMED) is proposed by Qiu et al. [14] for improving the reliability of vehicle-assisted communication. TMED is modeled on the basis of the spider web concept, where the spider agents are responsible for discovering communication routes to the destination.

Similarly, TMED harmonizes dynamic multi-priority message queue management and confined greedy forwarding for reducing end-to-end latency and routing overhead with better packet delivery.

Shah et al. [15] introduced a time barrier based vehicular data dissemination mechanism for reducing the complexity in handling emergency messages. Along with the super-node, this dissemination mechanism suppresses broadcast storm issues improving the swiftness in data transmission and coverage.

Huang et al. [16] designed an infrastructure-to-infrastructure based forwarding mechanism for improving the communication rate of vehicular networks. Communicating vehicles are selected based on a determined cost metric. The cost metric is estimated on the basis of energy exploitation and delay estimation. Besides, the infrastructure employs a threshold based decision strategy for identifying reliable vehicles achieving less processing complexity.

An adaptive emergency message broadcast strategy is introduced by Chou et al. [17] for reducing the latency in vehicular ad-hoc network communications. To ensure the precise transmission of emergency messages, non-redundant broadcasts are encouraged by the vehicles. With the fore-hand assignment of back-off timers, the waiting time is assigned for the sequential forwarders, ensuring transmission reliability with better response.

Qiu et al. [18] designed a efficient data emergency aware scheduling scheme for improving the response rate in less time latency for IoT incorporated smart cities. This scheduling scheme determines the emergency of the data on the basis of priority and time deadline. The transmission sequence is acknowledged by the destination after receiving the emergency information from the source. This scheduling reduces packet loss, waiting time and latency.

Multi-hop clustering approach over vehicle-to-internet (MCA-V2I) is projected by Senouci et al. [19] for improving the performance of vehicular communication network. Clustering is performed by gaining neighbor information by establishing connection to the cloud via infrastructure. The constructed routes are then traversed using breadth first search algorithm consenting the mobility factors. This approach improves delivery ratio by reducing delay and overhead.

Mahmood and Horváth [20] elaborated the dissemination of alert messages in a highway vehicular network scenario. The authors concentrated in suppressing the issues in message dissemination due to distance factor by balancing the impact of vehicle speed. Besides, an effective queuing system is also incorporated to address traffic congestion problem.

Adaptive routing protocol based on reinforcement learning (ARPL) is designed by Wu et al. [21] for leveraging the performance of multi-hop communication in vehicular ad-hoc networks. With the help of periodic HELLO messages and the Q-learning algorithm observed the link status between the vehicles. Packet restructuring and MAC layer feedbacks are used for preventing routing loops and adaptability in vehicular communication. Simulation results prove the consistency of the proposed ARPL by improving packet delivery ratio and reducing delay and routing hops.

Hassan et al. [22] introduced a multi-metric geographic routing (M-GEDIR) for retaining the endurance of the communication links in vehicular networks. The endurance of the links are retained by selecting neighbors on the basis of signal strength, next position, speed and distance, and collision causing communication range. The additional metrics considered for neighbor selection helps to retain the lifetime of the links reducing link failure, connection delay and improving throughput.

Multi-Model Tree –driven transmission (MTT) Scheme

MTT is designed to handle challenges in IoV medical data transmission and vehicle level communications. In this article, data dissemination errors due to routing loops and communication stagnancy are addressed. The fundamental theme is to organize vehicular communication with the help of cloud services for better medical data handling. For example, an ambulance vehicle with smart communication features is expected to deliver timely and reliable monitoring messages to the hospital/ health center. The communicating smart vehicle is responsible for ensuring reliable data transmission suppressing routing constraints. This transmission scheme is designed to augment vehicle-to-vehicle communication even in the absence of infrastructure units. Figure 1 portrays a general IoV scenario with the functions of MTT.

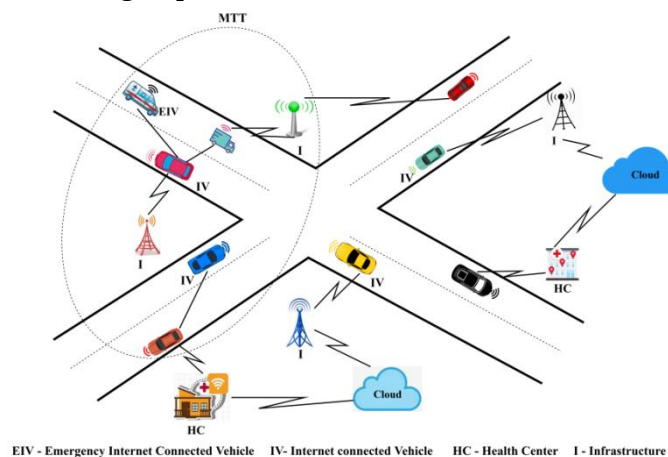


Figure 1 IoV Scenario with MTT Representation

II. Methodology

The proposed MTT is packed with two working phases namely

- (i) Neighbor selection
- (ii) Data dissemination

Both the phases are operated in a sequential manner to ensure loop free non-stagnant data dissemination. Precision in neighbor selection and data communication management are preceded by exploiting the multi-attributes of the vehicles. Independent decisions in routing at the intermediate IV is assisted using global positions from the internet. In the following section, the two working phases are explained briefly.

(i) Neighbor Selection

In this phase, vehicle selection for forming communication routes to the destination and internet connected vehicles is constructed over vehicular ad-hoc networks. The vehicles forming the elements of communication are autonomous and self-configuring. The vehicles communications are also interfered due to the resource-constraint nature of the network. Mobility pattern, vector and magnitude of the vehicles are dynamic and hence communication is pursued through different routes to the destination with time. However, this increases the communication latency and routing loops by is identifying a same neighbor through different broadcasts. In this proposal, the multi-model attributes of the vehicle is assessed through support vector classification for predicting its next available neighbor. With the definite neighbor information, routing loops are discarded by formulating a one-to-one connected tree-driven route. The output of the classification process is to identify disjoint forwarding neighbors based on the moving direction of the EIV. The conventional mathematical expressions are given as follows: Let d represent the distance

between two vehicles $v1$ and $v2$, moving in a direction $(\Delta x1, \Delta y1)$ and $(\Delta x2, \Delta y2)$. The angle of departing (θ_d) between $v1$ and $v2$ is expressed as in equation (1)

$$\theta_d = \arccos \left(\cos \frac{\Delta x1 \cdot \Delta x2 + \Delta y1 \cdot \Delta y2}{\sqrt{\Delta x1^2 + \Delta y1^2} \cdot \sqrt{\Delta x2^2 + \Delta y2^2}} \right) \quad (1)$$

If the θ_d between two vehicle's $v1$ and $v2$ is same, then the vehicles are said to be in the same lane/road segment. The requirement is to ensure if the vehicle is moving away/ towards its neighbor, for communication. Now, another metric, the path validity time (p_t) is given as

$$\left. \begin{aligned} p_t &= \arg \max \{ LET_{ij} \}, i, j \in \{IV\} \\ \text{and} \\ Let &= \frac{-(pr+qs) + \sqrt{(pr+qs)^2 - (p^2+q^2-R^2)(r^2+s^2)}}{r^2+s^2} \\ \text{where,} \\ p &= x_1 - x_2, q = y_1 - y_2, \\ r &= vel1_x - vel2_x, s = vel1_y - vel2_y \end{aligned} \right\} \quad (2)$$

Where, ET is the path expiry time, (x_1, y_1) and (x_2, y_2) are the location/position co-ordinates of $v1$ and $v2$ respectively. The variables $(vel1_x, vel1_y)$ and $(vel2_x, vel2_y)$ denote the velocity of $v1$ and $v2$ in x and y -axis respectively. The aim of routing is to select a neighbor with minimum ET or satisfying p_t . For a set of n vehicles along the transmission path, $(n-1)$ links are available. The challenge in formulating route is the replicated vehicles in the path due to its position, velocity and acceleration. Depending on these features, p_t and path stability p_s are determined. The path stability factor is determined using equation (3)

$$p_s = 1 - e^{\frac{-2 \cdot ET}{p_t}} \quad (3)$$

Similarly, the displacement of the vehicle is subjected to change at definite time instance t . The impact of these attributes over p_s is balanced using vector classification between the vehicles moving away/ or moving towards the EIV. The marginal classifier boundary of the SVM process segregates the two types of

vehicles for balancing p_t and p_s suppressing the variation due to position, velocity and magnitude. The solution is modeled in the communication space as represented mathematically in equation (4)

$$y = ax + b$$

such that

$$y - a - ax - b = 0 \text{ is the standard representation} \quad (4)$$

The solution space lies in $y - ax - b$ plane. The default hyperplane with solution space is illustrated in Figure 2(a)

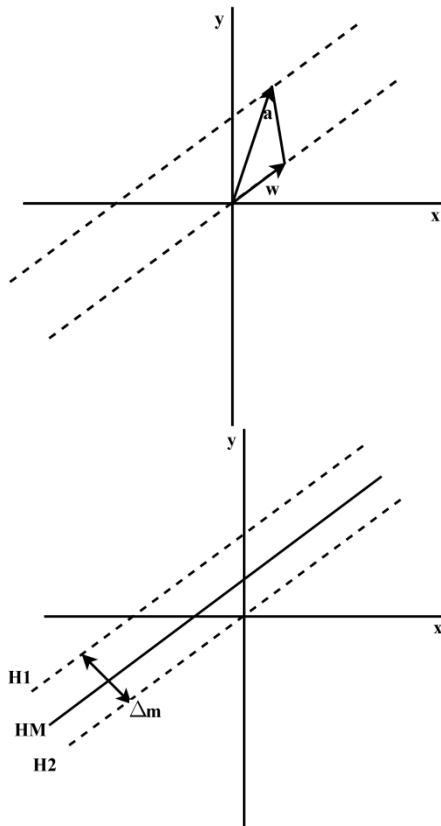


Figure 2(a) Default Solution Plane
2(b) Marginal Separation of H1 and H2

The value w represented in Figure 2(a) represents a normalization vector concurrent to the hyperplane. In figure 2(b), the marginal separation (HM) of the two planes $H1$ and $H2$ is illustrated. Let $H1$ represent the plane consisting of vehicles moving in an opposite direction post intersection. $H2$ represents the plane separating the vehicles moving in the

same direction. Let v_n represent the qualified vehicle such that

$$\begin{cases} v_n \cdot x = +\gamma, \text{ for vehicles in } H2 \\ v_n \cdot x = -\gamma, \text{ for vehicles in } H1 \end{cases}$$

(5)

Where γ is the hyperplane offset. Different from the conventional classifier model this proposal does not include any optimum weights. The reason for discarding weights is the dynamicity of the vehicles and the associated features. The conditions and other prospects of the vehicle with appropriate classification ($H1|H2$) are given in Table 1.

Table 1 Condition, Variation and Plane Representation

Condition	θ_d variation	Plane Representation	
Vehicles are moving towards each other (opposite direction)	$0^\circ \leq \theta_d \leq 180^\circ$ In I and II Quadrants	IV 	I 
	$181^\circ \leq \theta_d \leq 360^\circ$ In III and IV Quadrant	III 	II 
Vehicles are moving in the same direction	$0^\circ \leq \theta_d \leq 180^\circ$ In I and II Quadrants	IV 	I 
		III 	II 

The vehicles in III and IV quadrants (same direction) are discarded while possessing same direction of movement. This ensures data forwarding in the direction of EIV as it heads towards the hospital/health center. The variation between $H1$ and $H2$ is Δm that determines the support vectors for neighbor vehicle selection. The varying distance between two hyper planes is given by

$$\left. \begin{array}{l} \Delta m = 2 \times \frac{1}{d(i,j)}, \quad i \in H1 \\ \text{Such that} \quad j \in H2 \\ d(i,j) \leq R(i) || R(j) \quad \text{or} \\ \text{Vice - versa} \end{array} \right\} \quad (6)$$

Where d is the distance between the vehicle i and j respectively. Now, the vehicles forming the margin of $H1$ and $H2$ are considered for communication. On the other hand, the vehicles located within Δm are discarded as the vehicles in $H2$ moves to $H1$. In this case, the vehicles are displaced by $181^\circ \leq \theta_d \leq 360^\circ$, behind the EVI and therefore it is discarded. Consider a set of routing paths $p = \{p_1, p_2, \dots, p_n\}$ that leads to the hospital. Each path consists of n vehicles and $(n - 1)$ links such that the chance of route joins is $n(n - 1)$. This route join probability estimated is the maximum achieved replication that decreases with $H1$ and $H2$ classification. A boundary vehicle (support vector if enters the mediate region Δm based on its position and velocity, then the chances of $n(n - 1)$ decreases. This reduces the intersecting neighbor interference, though the routing path count is decreased. The routes that are disappeared due to the position of the vehicle are discarded to discover a new neighbor entering the I and II quadrants satisfying $0^\circ \leq \theta_d \leq 180^\circ$. Now, the multimodel attributes such as $(x, y), ET, vel$ and $x + t, \Delta y + t$. Let α represent the set of attributes such that the information reliability through the associated vehicle is required to augment the vehicle in the routing in the routing path. The information reliability (I_{RL}) is given by equation (7) as

$$\left. \begin{array}{l} I_{RL} = E(\alpha) - E(\alpha)_i, i \in \{\alpha\} \\ \text{where,} \\ E(\alpha) = \sum_{i=1}^n \rho_i \log_2 \rho_i \\ \text{and} \\ E(\alpha)_i = \sum_{j=1}^t \frac{|\alpha_i|}{|\alpha|} \times E(\alpha_i) \end{array} \right\} \quad (7)$$

Where, $E(\alpha)$ and $E(\alpha)_i$ are the entropy of the entire set α and individual attribute $i \in \alpha$. The factor ρ_i represents the probability of selecting

a vehicle in the path p . I_{RL} for vehicles in Δm are not considered as the vehicle enters non-feasible transmission state. Vehicles satisfying $[d(i, j)\Delta m] - \Delta m$ condition (i.e.) the hyperplane $H2$ is present away from Δm are opted for forming the routing path. With the estimated I_{RL} , the p_s of the current path p (hop-by-hop) with the joining of the vehicles is estimated to select $\max\{I_{RL}\}$ and $\max\{p_s\}$ condition satisfying neighbor. A conventional transmission tree satisfies the above condition in all the levels. The prime condition informing the routing tree for transmission is to neglect neighbors present in Δm . Therefore, the routing tree is defined as a uni-directed graph $G = [n, (n - 1)]$ such that $n \in 0^\circ \leq \theta_d \leq 180^\circ$ and $\notin \Delta m$. Similarly, $(n - 1)$ of a 'n' is not the same with another n . The entropy of α and each element, $i \in \alpha$ is estimated in cumulative and independent manner (equation (7)) with respect to the vehicles (n) in the path p and different time instance (t). The variation of the entropy with respect to n and t are pre-estimated to suppress additional transmission latency due to neighbor selection and replacement. The depth towards θ_d of the hospital / health centre decreases with the displacement $(x + t, y + t)$ of the EIV. The next level of neighbors with the updated position is accessed from the internet cloud where the other IV store their information/ Therefore, path planning and tree-reconstruction on the basis of location, displacement is assisted using cloud data that is proceeded by the support vector classification process. This helps to retain sufficient disjoint routes to the destination, reducing route disconnection. As the vehicles are selected based on classified I_{RL} unnecessary broadcast and frequent neighbor (forwarder) replacement is confined, reducing transmission complexity. The representation of the uni-directed tree using classified I_{RL} is represented in Figure 3.

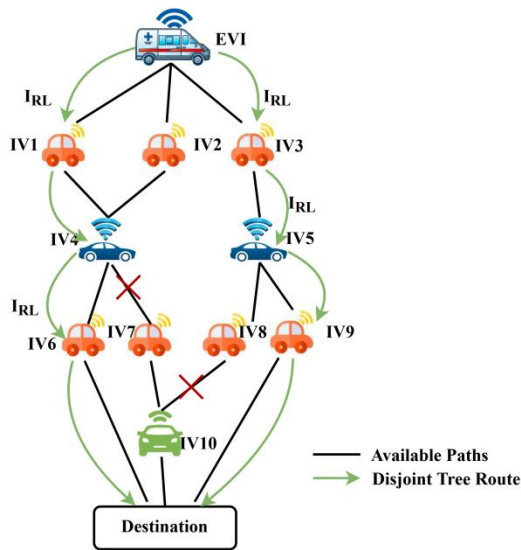


Figure 3 Uni-Directed Tree Representations

In Table 2, the density of vehicles and their classification as per H1, H2 and I_{RL} observed in the simulation is summarized.

Table 2 Vehicle Classification

Vehicle Density	H1	H2	I_{RL}	Paths
10	1	8	5	1
20	6	12	7	2
30	11	16	12	2
40	19	14	3	1
50	16	28	17	4
60	23	36	23	7
70	17	48	39	6
80	39	36	24	4
90	23	59	48	8
100	36	67	53	7
110	44	61	47	6

(ii) Data Dissemination

The formulated tree based routing is exploited for transmitting health information to the destination. In this phase, the classified neighbors are permitted to make intermediate decisions with help of cloud-stored information. The intermediate tree neighbors perform decision making for reducing the stagnancy in message transmission. Let $t_m(d, y)$ represent the time for delivering a message 'm' through the neighbor y across a distance 'd'. The

distance is subjected to change with the phase is to achieves less transmission latency (i.e.) $\min\{t_m(d, y)\}$. The cumulative latency is estimated as

$$\sum t_m(d, y) = \rho_i [t_q + t_t + \min\{t_m(d, y)\} t_m(d, y)] \quad (8)$$

Where, t_q and t_t are the queuing and transmission time. From equation (8), it is clear that the latency holds of vehicles where $\rho_i = 1$ else the there is not transmission. Stagnancy in message dissemination occurs due to collision and improper transmission schedule. Collision probability (ρ_c) is estimated using equation (9)

$$\rho_c = 1 - \left[\sum_{i=1}^X (1 - \rho_t) \frac{(4\sigma R)^n}{n!} e^{-4R\sigma} \right] \quad (9)$$

Where σ is the poission distribution representing the density (population) of the vehicle, X is the total dissemination ρ_t is the transmission probability computed using equation (10)

$$\rho_t = \frac{2 \times (1 - e^{-\beta t_m(d, y)})}{c_w + 1} \quad (10)$$

Where, β denotes the message density per unit time (seconds) and c_w is the contention window size. The successful data delivery (ρ_{del}) is estimated through all the available disjoint paths

$p_{dis} \in p$ as

$$\left. \begin{aligned} \rho_{del} &= \sum_{i=1}^{p_{dis}} i - \prod_{i=1}^{p_{dis}} i \\ &\text{such that} \\ \rho_{del} &\leq \max\{i\}, i \in p_{dis} \in p \end{aligned} \right\}$$

$$(11)$$

The rate of message delivery retained at different transmission intervals in retained in the data dissemination phase ensuring all the medical data is handled and relayed to the health center. The above discussed collision probability is estimated for σ in the possible intersections. The vehicle follows Manhattan

mobility model in which the vehicle adopts a maximum collision of $(4 \times \sigma)$ density of vehicles and a density of σ . In such scenarios, the number of new neighbors is high granting a chance for tree alteration. Contrarily, the proposed method discards the request of the new neighbors to preserve the current transmission. Besides, the attributes of the new neighbors are yet to be classified and it provides an asynchronous dissemination for the rest of the data. Therefore, the intermediate vehicle takes responsibility of streamlining the transmission synchronized with the transmission time. The transmission slots are organized depending upon the t_q at each level of the tree. The transmission slot (t_s) is given by equation (12)

$$t_s = t_b + t_c + t_a + t_t + t_q$$

(12)

Where, t_b, t_c and t_a are the burst time, contention time and acknowledgement time. Here, there is no acknowledgement since the EIV monitors and transmits medical information to the health Centre, and therefore, t_s relies on the sum of burst, contention, transmission and queuing time of the health data. To retain the reliability in data dissemination, a local decision-making process is defined for the IV in p_{dis} . The first data dissemination slot is modelled in a sequential manner for all the path nodes as illustrated in Figure 4(a).

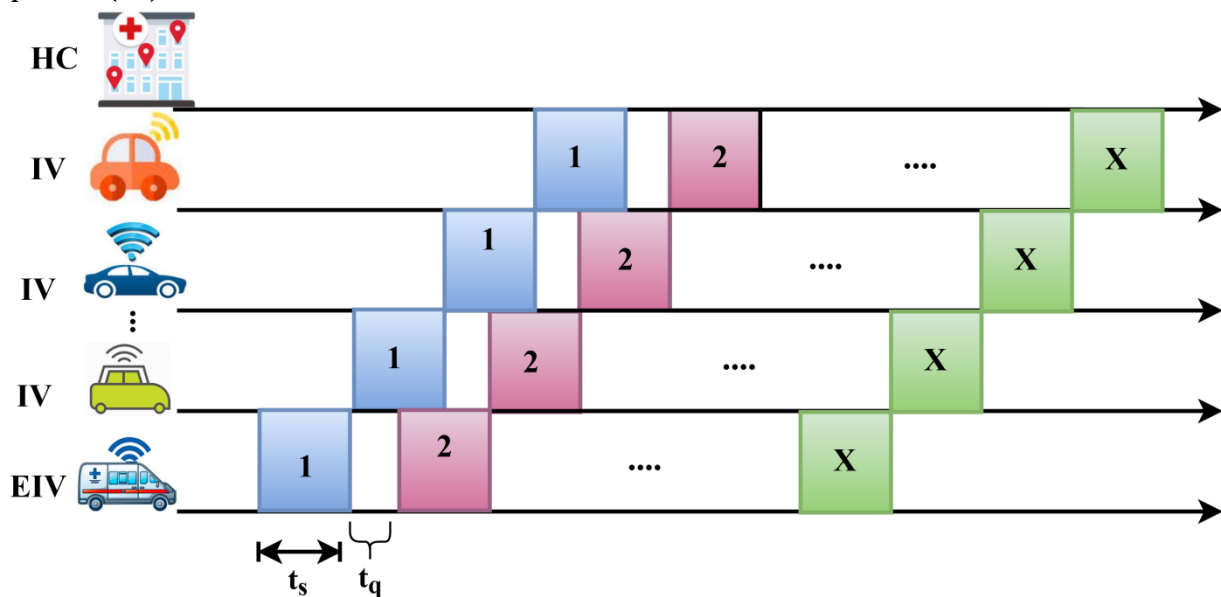


Figure 4(a) Sequential Dissemination

If an intersection is encountered, there are new neighbors that are ready for augmenting p to the destination. Like the routing in conventional vehicular networks, if a new neighbor is switched-over, it results in increased t_q and hence the number of detained health data increases. This creates backlogs in communication and also degrades data delivery. Therefore the IVs relay on less-complex decision-making process to classify the new neighbors based on $H1$ and $H2$ planes. This

classification is processed in a parallel manner with the existing data dissemination without interfering communication. The classification of IVs is sent as recommendations to the EIV. If the identified new neighbors possess a better solution than the current tree path, then EIV switches its transmission through a newly furnished route through the intersecting vehicles. The IVs frame a set of rules for the new vehicle selection and are explained below:

Rule 1: new vehicle $\in H2$ plane with maximum variation in $[d(i,j) - \Delta m] > \Delta m$.

This ensures that the new vehicle is not a support vector but also a member in $H2$ plane. The direction of movement of the vehicle can be either towards or opposite to the EIV.

Rule 2: The displacement $\Delta x + t, \Delta y + t$ must be coherent with the EIV.

In this rule, the direction of the vehicle is determined (i.e.) the vehicles satisfying rule 1 are filtered based on the direction of movement. Vehicles with same moving direction are preferred to join the new path.

Rule 3: The information reliability of the new vehicle must be greater than the existing path vehicle.

If rule 3 has to be satisfied, then at least one attribute of the vehicle must possess profitable entropy. A profitable entropy is estimated on the basis of t_m and t_q . Obviously, the queuing delay of the vehicle must be less such that it accepts new slots to handle more data, vehicles passing the above rules in a step-by-step manner are recommended for establishing new disjoint tree routes to the destination. In such case, the second/alternate dissemination time slot is modeled from the t_q between two transmission slots as represented in Figure 4(b)

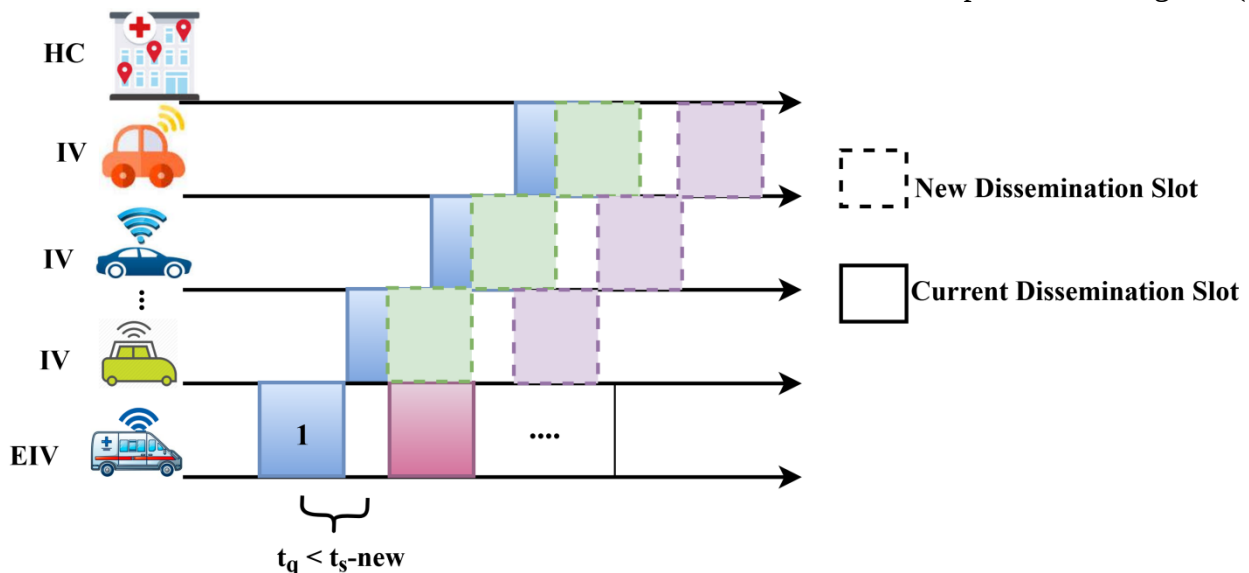


Figure 4(b) Alternate Dissemination Slot

As the dissemination slot follows parallel transmission without interrupting the communication of the current slot, the rate of medical data handling is high. More specifically, the detained messages in dissemination are less by differentiating sequential and alternate dissemination slots reducing the un-served messages.

Performance Evaluation

The performance of the proposed MTT is evaluated using experiments modeled using network simulator with SUMO traffic generator. In this experimental analysis, a

maximum of 500 internet connected vehicles are placed in an open street map of region $4 \times 3 \text{ Km}^2$. The rest of the experimental setup and its values are tabulated as follows.

Table 3 Experimental Setup and Values

Experimental Setup	Value
Mobility Model	Manhattan Mobility Model (MMM)
Control Message Size (b)	128
Population	10-110 vehicles/ Km
Data Dissemination Rate (Mb/s)	40

Infrastructure Units	12
Healthcare Data Size	160
(b)	
Velocity of IV (m/s)	20-60

The analysis of the results for the metrics delivery ratio, transmission latency, disconnection ratio, messages transmitted, backlogs, and transmission complexity is compared with the existing TMED [14], SD-IoV [11] and IARAR [12].

Average Delivery Ratio Analysis

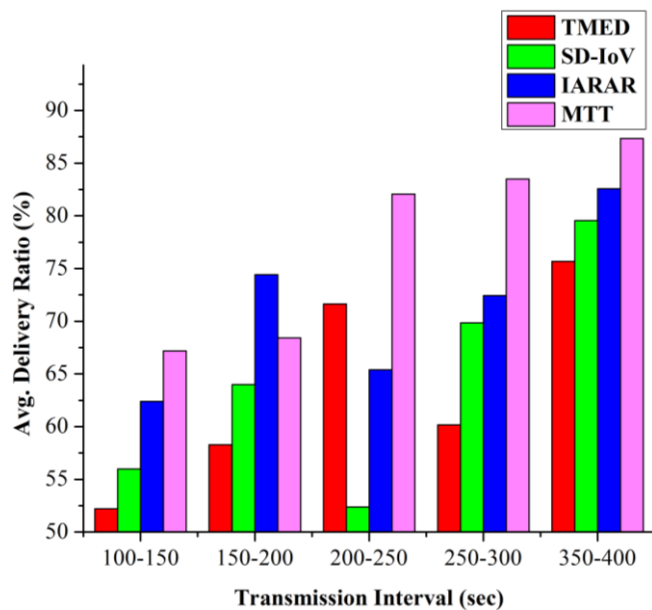


Figure 5 Average Delivery Ratio Comparisons

The rate of messages struck in replicated path vehicles and routing loops is evaded by framing tree-based routes to the destination. Post the process in neighbor selection phase, data dissemination follows un-interrupted transmission slots reducing the rate of data loss. In addition to these features, delay in neighbor selection. Route stability and collision probability are suppressed through SVM classifier and local decision-making process. The procedure is followed unanimously in all t_s such that successful data delivery is ensured. Similarly, the factor ρ_{del} ensures maximum data dissemination by segregation disjoint routes from the available paths to the

destination. Therefore, $\rho_{del} \leq \max\{1\}, \forall i \in p_s \in p$, improving the delivery ratio at different time intervals (Refer Figure 5).

Average Transmission Latency Analysis

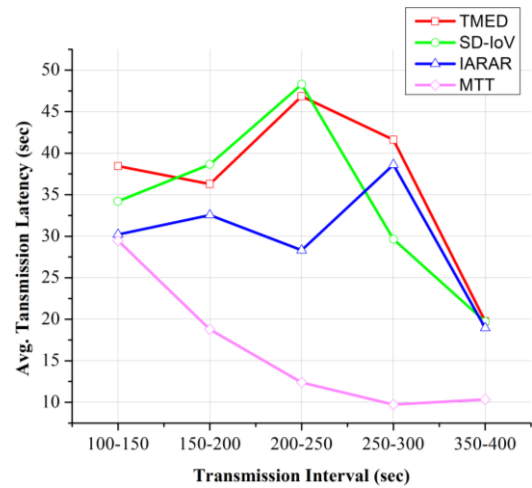


Figure 6 Average Transmission Latency Comparisons

Figure 6 portrays the comparison of transmission latency against different transmission intervals. In this monitoring and updating scenario, $t_a = 0$ and the t_q is less until a road intersection/new vehicle population is encountered. If a new intersection/population is encountered, the new t_s is framed is parallel to the existing sequential slot. The new slot is sent as recommendation to the EIV such that it demands I_{RL} from any of the considered multi-modal attributes of the new neighbors. The present communication is not detained in any t_s such that is either replaced /discarded. More specifically, the new dissemination slot is adapted between $2t_s$. This ensures $t_q < t_s$ new for the entire new vehicle concentrated path. Similarly, the vehicles leading to delayed transmission are discarded on the basis of decision rules followed by IV. These constructive features help to achieve less transmission latency.

Analysis of Disconnection Ratio

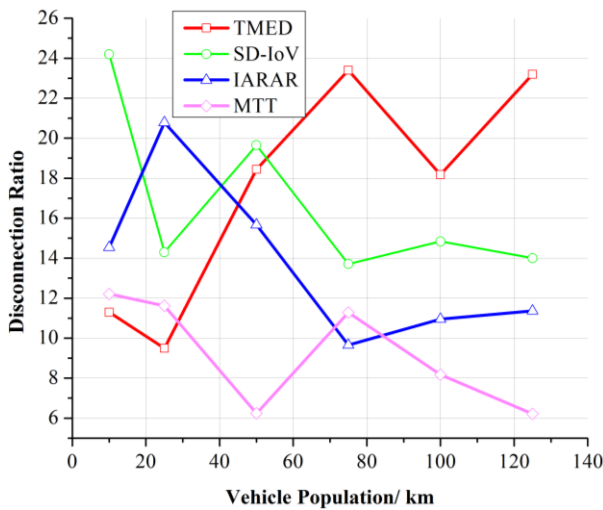


Figure 7 Disconnection Ratio Analyzes

In the Figure 7, a comparative analysis of disconnection ratio between the existing methods and proposed transmission scheme is presented. The rate of disconnection increases with road intersection and collision probability. In the proposed transmission scheme, the short lived routes are classified using Δm , $H1$ and $H2$ analysis. Also, the selected neighbor satisfies p_s ensuring prolonged connectivity. In case of replacing transmitting neighbors and dissemination slots, rule 1 to rule 3 is followed such that the obtained I_{RL} is relatively high. The information reliability relies on p_s and θ_d along with the velocity and displacement of the vehicle. Therefore, both classified vehicles and rule driven vehicles are unanimously selected to satisfy p_s and p_t ensuring better path stability. AS path stability is high, the rate if disconnected is less in MTT. Also, this stability is not disturbed by the p_c and p_t parameters estimated in t_s .

Analysis of Message Transmitted

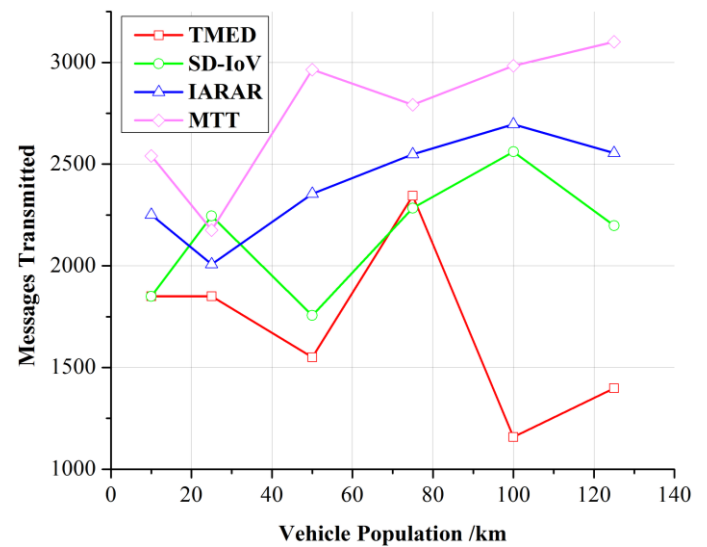


Figure 8 Messages Transmitted Analyzes

The number of healthcare messages transmitted by the EIV and IV is high. This is achieved by streamlining the transmission slots and ρ_c at every t_s . Communication at the time of encountering new vehicles and intersection degrades the dissemination slots by increasing congestion. In MTT, the vehicles pursuing t_s are separated by following the rules of neighbor selection in the local decision process. This helps to achieve less transmission failure retaining the number of data /messages handled in a like manner. On the other hand, the parallel t_s of the new neighbors augments non-colliding data transmission from IV to the destination. Therefore by optimization t_s and ρ_c , better transmission is achieved in the proposed MTT (Refer Figure 8).

Analysis of Backlogs

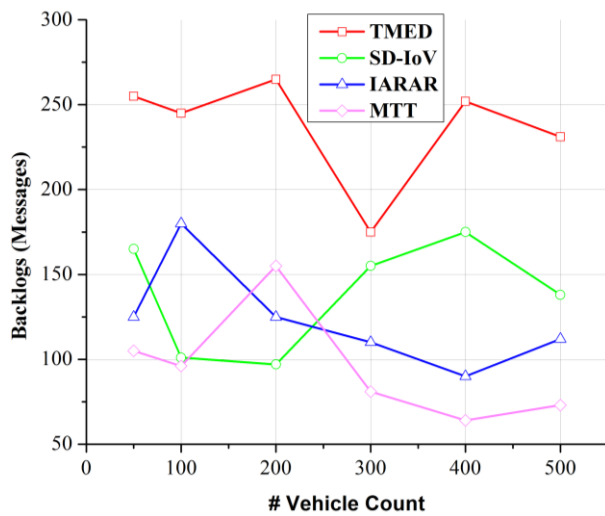


Figure 9 Backlogs Comparison

The message retained at the IV level without drop or delivery is estimated as backlogs. Some methods adjust the size of the contention window c_w to stand collision, experiencing delay. In MTT, the classifier distinguishes vehicles on the basis of direction initially. The local decision process filters reliable information centric neighbors for data dissemination. In both the phases, lag in transmission due to vehicle attributes and collision is suppressed. This improves the rate of data dissemination controlling the backlogs in communication. In all the allocated t_s the fore-mentioned features are unanimously followed throughout the dissemination process to reduce backlogs (refer Figure 9).

Transmission complexity Analysis

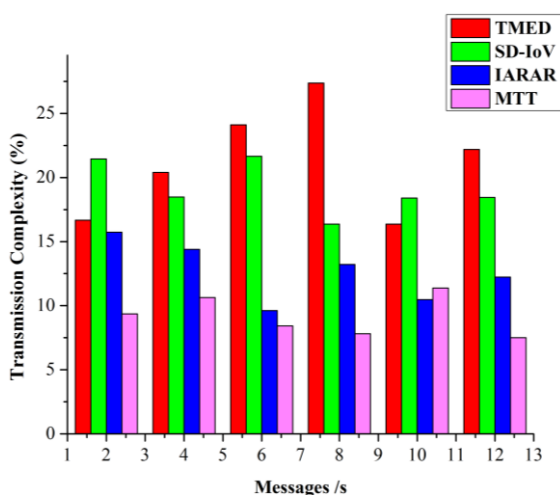


Figure 10 Transmission Complexity Analyzes

Figure 10 depicts the comparative analysis of transmission complexity between the existing and proposed schemes. In the proposed MTT, disjoint tree-based path selection reduces the chances of data duplication and control message replication. The paths are filtered by classifying vehicles under $H1$ and $H2$ planes of the SVM classifier. Therefore, the available paths are filtered based on the direction of vehicle movement. In the dissemination phase, rule satisfying neighbors with better I_{RL} is selected refining the relevant vehicles. In both the phases, reliable neighbors are selected for transmission with disjoint routing ability, reducing transmission complexity. It is to be noted that the available neighbors are not replaced on encountering ρ_c like the conventional methods. This also helps to reduce transmission complexity in MTT.

III. Conclusion

This article presents a multi-modal tree-driven transmission scheme for optimizing data handling and dissemination of healthcare IoV. Neighbor selection and data dissemination is independently performed with the aid of support vector machine classifier and local decision making process for reducing transmission complexity. The neighbors and path vehicles are filtered on the basis of direction in the selection phase and the intersecting neighbors are filtered based on communication beneficial rules in the data dissemination phase. These phases harmonize message / medical data handling and dissemination rate suppressing the issues due to collision and non-disjoint routes. Performance analysis of the proposed MTT results in strengthening the proposal by achieving better delivery ratio, message transmission reducing backlogs, transmission latency and disconnection ratio.

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