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Distributed Estimation Framework for Beyond 5G Intelligent Vehicular Networks

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ABSTRACT Intelligent vehicular networks (IVNs) have drawn substantial interests in recent years due to its great potential in enabling diverse applications in the fifth-generation (5G) and beyond communication systems. In IVNs, vehicles are equipped with multi-functional advanced wireless sensors which are capable to collect real-time and practical environmental information. In this paper, we first provide an overview of the existing researches on IVNs for beyond 5G (B5G) communications, while emphasizing the requirements and technical approaches. To fully unleash the potential of vehicular intelligence, smart vehicles should acquire the values of some important variables of interest, e.g. traffic volume in the network. Thus, we introduce a generalized framework which formulates the acquisition of desired variables as a joint estimation and detection problem. Our framework adopts factor graph to solve problems in IVNs. This is done by collecting the observations from vehicles at road side units (RSUs) for inferring such variables and sending them back to vehicles. Nevertheless, this centralized framework critically depends on the functional reliability of the RSUs. To this end, we propose a distributed estimation framework to improve the scalability and robustness, in which vehicles can communicate wirelessly with other vehicles within the communication range. Then, we introduce different consensus operations as a realization of this proposed framework and briefly compare them in terms of implementation feasibility and convergence behavior. Three approximation schemes are further considered for reducing the required communication signaling overhead. To shed light on the proposed distributed estimation framework, we focus on two cases, i.e., target tracking and network decoding in IVNs. Through simulations, we show that the distributed algorithms can efficiently track the target and decode the broadcasted messages, while achieving the same performance of the centralized schemes. Finally, important conclusions are drawn and some challenges and open problems in this research area are outlined.

INDEX TERMS Beyond 5G, intelligent vehicular networks, distributed estimation, factor graph, consensus, target tracking, network decoding.

I. INTRODUCTION

After years of research and development, the fifth-generation (5G) wireless communication systems have finally been globally standardized and commercialized. One of the three cores of 5G application scenarios is massive machine-type communications (mMTC) for the internet-of-things (IoT) services [1], [2]. In particular, vehicle-to-vehicle (V2V) communications is one of the most challenging tasks in mMTC scenarios which require massive connectivity and reliable transmissions in a high-mobility environment [3]. Furthermore, car industry has significantly developed over the last decades and will continue to do so in the near future. It is expected that in beyond 5G (B5G) wireless communication systems, V2V communications will play an even more important role, as vehicle transportations will be more intertwined with people's daily lives. To fulfill the stringent quality of service (QoS) requirement in B5G, the intelligent vehicular network (IVN) is considered as one of the prominent enablers due to its "social" characteristics of sharing information between vehicles [4].

An IVN is a type of vehicular networks which possibly connects various vehicles, back-end systems, and infrastructure components, such as road side units (RSUs), to provide a variety of benefits including improved traffic management, road-safety, and the support for partially autonomous vehicles and infotainment services [5]. The success of IVNs relies on the exploitation of advanced wireless sensors to acquire the real world information such that vehicles in the IVNs can make prompt changes and decisions accordingly by sharing information ubiquitously over the network. In particular, the rapid development of car industry enables the massive deployment of sensors installed in vehicles, such as cameras and radars, which facilitates smart vehicles to obtain a large amount of information of its surroundings. The collected information is then communicated through the wireless network with the support of additional infrastructure components, such that complex applications, e.g., target tracking, can be made by the vehicle network in a collectively manner.

In the era of B5G, IVNs can support advanced applications regarding the road safety and traffic management. In specific, those applications can be classified into three groups, namely road safety applications, traffic management applications, and mobile Internet applications [6]. In the following, we will discuss these three applications and the related information to be estimated and detected in IVNs.

Road safety applications aim to reduce the probability of accidents in traffic, such as vehicle collisions at intersections. Through information sharing between vehicles and RSUs, the influence of drivers' misbehaviors and poor road conditions can be greatly mitigated. Such information may contain different important messages such as vehicle speeds, vehicle positions, road conditions and potential hazards, etc. Based on these messages, the IVN is capable of making appropriate decisions to enhance the road safety by estimating and detecting vehicles' state. Some examples of road safety applications are discussed as follows [6].

- Collision-prevention: In this use case, safety instructions are sent by vehicles or RSUs, where collision-related warning messages belong to an important type of information to ensure the road safety. For example, the intersection collision warning can be sent by RSUs to approaching vehicles to reduce the risk of potential collisions; Lane change warning and overtaking vehicle warning are a type of messages sent from vehicles to its neighboring vehicles to prevent possible collisions during the lane changing and overtaking; Hazardous location notification and signal violation warning are messages sent by RSUs to vehicles to indicate poor road conditions to alert drivers to react accordingly; All above tasks require accurate estimation of the vehicle location, and precise detection of the vehicle state.
- Loss-control: In this use case, warnings and instructions regarding inevitable crashes are broadcasted to minimize the influence of the crash. For example, pre-crash warning is a message sent by a vehicle, which is going to experience an inevitable crash, to RSUs and neighboring vehicles. This message may contain the predicted crash location, which can be exploited to reduce the impact of a crash; Collision risk warning is a message broadcasted by RSUs towards all neighboring related vehicles in the case where a crash happens between two or more vehicles that are not able to communicate due to the crash; In such tasks, the warning message should be detected with high priority and reliability.

Traffic management applications help the administration of IVNs in terms of the traffic flow and coordination from a network perspective. Specifically, traffic management applications provide user location information and other related information for efficient traffic control.

- Traffic control and scheduling: In this use case, control and scheduling messages are broadcasted in the IVN. It may contain specific information such as speed management message, traffic condition warning, and scheduling message. For example, scheduling messages can be sent to neighboring vehicles in order to free a lane for emergency vehicles with high-priority, such as ambulances and police cars. To optimize the traffic control and scheduling, the estimation as well as the prediction of the traffic volume in the IVN are demanded.
- Cooperative navigation: In this use case, automatic navigation messages can be generated based on the information gathered from other vehicles and RSUs. This type of application focus on enhancing the traffic efficiency through cooperation and scheduling.
- Social driving: In this use case, neighboring vehicles form a mobile social network, in which messages regarding social interactions among neighboring vehicles are broadcasted. Furthermore, social communities can be built among vehicles with common interests, including finding available parking spots, or heading to the same destinations. With the help of the mobile social network, the vehicles in the social communities frequently share information and cooperate with each other in order to improve the traffic efficiency as well as enhance the road safety. Hence, the detection of social messages is vital for the network.

Mobile Internet applications support passengers in the vehicles to have fast Internet services while on-the-go, in order to enjoy the journey. This includes instant messaging, video streaming, online gaming, and infotainment applications, etc. Specifically, these applications may either be supported by cooperative local services or global Internet services [6], [7]. In these applications, estimation and detection of the transmitted information with high accuracy are also required.

In order to support the aforementioned applications, IVNs need to meet certain requirements for signal detection and variable estimation based on the collected information. Therefore, the communication capability of IVNs is highly demanded. In particular, IVNs require reliable transmission with the support of a large number of individual users [8]–[10]. It should be noted that moving vehicles in the IVNs impose great challenges for data transmission and estimation. Firstly, robust data transmission is required in high-Doppler environments due to the high relative speed between vehicles. Secondly, the channel statistics vary rapidly since the locations of vehicles are different from time to time [11], [12]. Thirdly, establishing stable communication links between moving vehicles for a long time is challenging. Therefore, it is preferred to transmit a large amount of data in a short period of time. To overcome these challenges, recent developments of communication technologies become the key enablers. In the following, we will briefly discuss some possible technologies for realizing B5G IVNs.

Orthogonal time frequency space (OTFS) modulation is a recently developed technology, which has attracted substantial attentions since it was first proposed in 2017 [13]. Different from the conventional orthogonal frequency-division multiplexing (OFDM) modulation [14], [15], OTFS modulation focuses on a two-dimensional (2D) transformation, which efficiently converts the information symbols from the delay-Doppler (DD) domain to the time-frequency (TF) domain. This specific transformation not only provides a strong resilience against the channel imperfection due to the delay and Doppler, but also enables each information symbol to experience the full TF diversity [16]. Recent development of OTFS modulation includes the reduced-complexity detection method [17], the channel estimation algorithm [18], and pulse shaping design [19]. Due to its better performance than the conventional OFDM modulation in high-mobility scenarios, which can potentially enable vehicles to have reliable and robust communications, OTFS modulation is a promising candidate for IVN applications in B5G.

On the other hand, non-orthogonal multiple access (NOMA) has been recently recognized as a promising multiple access scheme [20]–[23]. In contrast to conventional orthogonal multiple access (OMA) schemes, NOMA allows multiple users to share the same degrees of freedom via superposition coding and successive interference cancelation (SIC) decoding. Therefore, NOMA can be employed in the IVNs to relieve the problem caused by severe access congestion and to enable massive connectivity. Besides, NOMA allows multiple vehicles to communicate with the infrastructure at the same time via the limited resources, which can effectively reduce the communication latency in the IVNs. A power-efficient resource allocation scheme for multi-carrier NOMA systems has been proposed in [24], where the power allocation, rate allocation, user scheduling, and SIC decoding order were jointly designed to minimize the total transmit power. The performance gain of NOMA over OMA was evaluated in [25], in which two types of NOMA's gain were identified and their performance trend in different communication scenarios are revealed. For an uplink NOMA system in [20], both the channel estimation and data detection were considered and a joint pilot and payload power allocation scheme was proposed to maximize the minimum effective signal-to-interference-plus-noise ratio (SINR) of each user [26]. The physical layer security for NOMA was discussed in [27], which fully exploits the inter-user interference for security enhancement. Yet, the introduction of NOMA complicates the problem of signal detection. In particular, multiplexing the users over limited resources invertibly induce inter-user interference. To this end, the multi-user detection problem for NOMA technology was investigated in the literature using different kinds of advanced signal processing algorithms, see [28], [29] and reference therein. An initial work on the employment of NOMA in vehicular networks was introduced in [30], which shows the potential of using NOMA for the IVNs in B5G.

Another promising technology is the faster-than-Nyquist (FTN) signaling [31], which is an efficient signaling method to enhance the spectral efficiency. In particular, FTN signaling intentionally introduces controlled intersymbol interference (ISI) by transmitting information symbols faster than the Nyquist rate [32]. It has been proved in [33] that such a signaling method can enjoy a higher channel capacity than that of conventional Nyquist signaling over the additive white Gaussian noise (AWGN) channels. To combat the severe ISI induced by the FTN signaling, various approaches with a reduced-complexity [34], [35] have been proposed in the literature. In [34], two reduced-search algorithms based on the Ungerboeck Bahl-Cocke-Jelinek-Raviv (BCJR) algorithm [36] were proposed. By performing Turbo equalization together with the channel decoder, FTN signaling with the proposed algorithms can achieve up to 163% of spectral efficiency gain with almost the same error performance. A comprehensive comparison between time-domain and frequency-domain equalization methods for FTN signaling was conducted in [37], which shows that the frequency-domain equalizations usually requires a lower complexity than that of the time-domain equalizations. However, the error performance of frequency-domain equalizations can be substantially worse than that of the time-domain counterpart. More importantly, FTN signaling has shown great potential in doubly-selective channels [38], [39] and in NOMA transmissions [40], [41], which aligns perfectly with the requirements of the IVNs.

Thanks to the recent development of communication technology, advanced communication capability allows information to be passed and received reliably and efficiently in IVNs. With the help of reliable communication, IVNs can support various applications by performing estimation and detection based on the received information. Several topics related to detection and estimation in vehicular networks have been studied in the literature. The estimation of road traffic density was studied in [42] and [43], where the analyses were conducted in terms of the accuracy of the estimation. Besides, the vehicular speed estimation was considered in [44] by measuring the received signal strength from nearby mobile

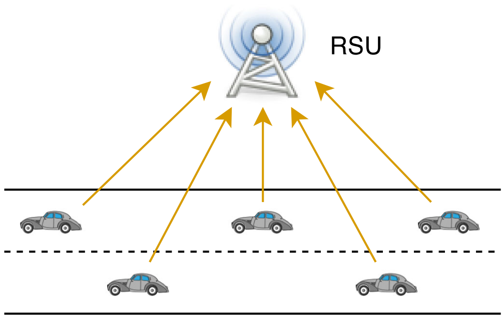


FIGURE 1. **The common protocol for realizing centralized processing. The arrows denote the information flow directions.**

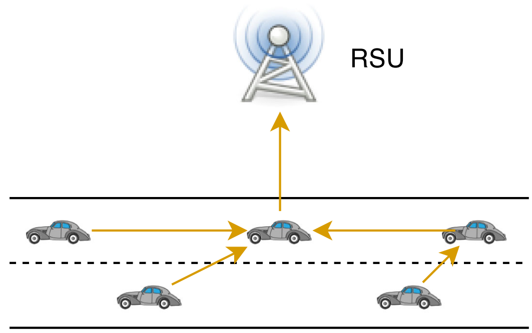


FIGURE 2. **A relay-based protocol for realizing centralized processing. The arrows denote the information flow directions.**

phones. In [45], a traffic accident detection algorithm was developed for reporting traffic accidents at intersections. In [46] and [47], the network agent localization as well as synchronization problems were investigated. To detect the misbehavior of vehicles in IVNs, several works were conducted from different viewpoints, which were reviewed in [48]. It is worth mentioning that the aforementioned detection and estimation problems in wireless networks, e.g. [43]–[48] assumed that a fusion centre is available for centralized information sharing and traffic control. For example, the vehicles produce the measurements related to the variables of interest after processing the raw data and send the measurements to RSUs via uplink transmission, as shown in Fig. 1. After collecting the observations from the vehicles, the RSUs can perform estimation and detection based on some advanced algorithms. Then the inferred variables of interest (referred to as the "global estimate") are sent back to the vehicles supported by the RSUs through down link transmission. Finally, the vehicles can take actions according to the estimates of variables to implement various applications in IVNs.

In B5G IVNs, it is expected that the number of wireless connected vehicles will be huge. In such a large-scale network, performing signal processing at a central unit is not preferred as it is not energy-efficient and economic-friendly. In the model illustrated in Fig. 1, if a vehicle locates far from the current home RSU, a high transmit power from the vehicle is required to achieve reliable reception at the RSU. In practice, reducing the required power is essential to save energy [49]–[52]. An alternative protocol for collecting the observations is depicted in Fig. 2, where distant vehicles communicate with the RSU relying on a routing scheme [53], [54]. In this case, some vehicles serve as relays under sophisticated network scheduling. The relay-based protocol can overcome the problem that a vehicle is not in the area of coverage of any RSU which reduces its energy consumption in the transmission. However, existing multi-relay protocols lead to a remarkable increase of signaling overheads and introduce excessive communication latency [55]–[57]. Besides, the assignment of serving as relays has to be updated frequently due to the dynamic property of networks. Moreover, when some of the RSUs are not working as intended, the whole network fails and causes severe performance loss or even jeopardizes the safety. To solve this problem, it is straightforward to perform estimation individually at vehicles based on their observed measurements. Apparently, the accuracy of the estimation results can not be guaranteed due to erroneous observations. This motivates us to establish a framework for IVNs that is scalable and robust to malfunctions of the RSUs as well as possible faulty measurements.

Recently, distributed estimation in wireless networks has drawn much attentions. Compared to the centralized method, the benefits of distributed estimation are two-fold: 1) it only depends on single-hop neighbor-to-neighbor communications and local computations,[1] thus is desirable for satisfying communication and energy constraints; 2) it provides the estimates of variables at each vehicle and enhances the fault tolerance of the wireless networks. Moreover, with careful design, adopting the distributed estimation method allows all vehicles to obtain the estimates of latent variables with almost the same performance as the centralized method. The direct decentralized solution is to share the measurements among the vehicles in the IVN then the vehicles are able to perform estimation. Strictly speaking, this is not a distributed scheme since each vehicle functions as a fusion centre. The concept of distributed estimation was firstly proposed in the pioneering works [58], [59], which focused on the control problem in large scale systems. Later on, more distributed estimation researches were conducted on the topics of hypothesis testing [60], nonlinear control systems [61], and mapping [62]. Most of the early works in this area depend on a hierarchical information fusion architecture which reconstructs the global estimate by fusing the local estimates. Under this architecture, the joint distribution of vehicles' measurements should be known and the local estimates are sent from the vehicles to a hierarchical processing unit, which are unrealistic due to the associated high communication cost. As a remedy, several works design distributed estimation algorithms under the constraint of limited transmission rate. For example, in [63], the transmitted signal from the network node is digitalized into several binary

[1]Two vehicle are said to be neighboring of each other if they are within the communication range.

bits. The authors of [64], [65] designed a class of sub-optimal estimators while the observations are quantized to one bit. To minimize the estimation error for a given transmission rate, the authors of [66] studied a distributed estimation mechanism by selecting appropriate quantizers in different scenarios. In addition to the rate-constraint problem, another issue for distributed estimation is the double counting of data, which will be discussed in the following.

The double counting of data is caused by the repeated use of the identical information [67]. Consider an example with two vehicles. The first vehicle updates its local estimate of a variable of interest based on its observations and broadcasts this information to the second vehicle. After receiving the broadcast, this estimate of variable is available to the second vehicle which is to be combined with the local observation of the second vehicle to update its estimation of variable. Similarly, this estimate is contained in the information broadcast and is received at the first vehicle. As the first vehicle has no knowledge that its local estimate was already embedded in the received information, it will update the local estimate based on the received information. Note that the local observations of the first vehicle in this process are adopted twice, which is known as data double-counting. In fact, in an IVN with multiple vehicles, some observations may be reused for several times, leading to a biased estimation results. To tackle this problem, some methods in [68], [69] were proposed to decorrelate the local estimates from vehicles in order to fuse only new information. For general wireless networks, by employing an information graph to exploit the topology of the network [70]–[72], the method of average consensus [73] was proposed to avoid the double counting.

The idea of average consensus, which originated from the field of automata theory and distributed computing [74], has attracted numerous interests for its applications in multi-agent/multi-vehicle networks [75], which can efficiently avoid the double counting of data and can facilitate the averaging of the vehicles' initial estimates. This is achieved by sharing their information between vehicles and iteratively update their local estimates. For instance, the work in [73] addressed the linear consensus problem in some new applications with fixed network topology. The authors of [76] then extended the fixed network to a time-varying one and developed a switch-based system model. For some practical applications, the convergence to an average of the local estimates is an essential requirement. To this end, researches on the development on convergence behavior has become another focus [77]–[79]. From the theorem of algebraic graph [80], in particular the graph *Laplacian* [81], the algebraic connectivity has shown to be efficient for analyzing the convergence of consensus algorithms. In [82], distributed consensus problems were addressed under a variety of assumptions on the network topology and the convergence analysis was also provided. It was shown that a properly chosen update weight guarantees the convergence after running a sufficiently large number of iterations if the associated algebraic graph is connected [82]. The *Laplacian* matrix of graph was also used for dynamic graphs by numerous researchers [83]–[85]. Note that the aforementioned works used a constant weight for all vehicles to update their local estimates. As the update weight is closely related to the convergence speed of distributed consensus, it is also very important to construct specific weights to accelerate the convergence. As a result, the metropolis weight was introduced in [86], which is capable of reaching consensus on the average of all local estimates from vehicles in a few consensus iterations.

On the other hand, belief consensus (BC), also known as likelihood consensus was developed for probabilistic model based problems [87], [88]. Instead of averaging the local estimates of all vehicles, the BC approach aims for obtaining the joint posterior or joint likelihood function concerning the variables of interest across the network via consensus operations. This is done by iteratively updating vehicles' local likelihood functions using the information broadcasted from their neighboring fvehicles. Compared to the conventional average consensus, BC is more suitable for statistical inference problems [89]. In [90], the authors proposed a BC algorithm for computing the joint likelihood function at each node. Relying on particle filtering (PF), a BC-based distributed algorithm was proposed in [91], which updates the weights of particles using the local likelihood functions (LLFs). A survey of distributed implementation of PF based on BC was provided in [92]. The authors of [93] studied the selection of update weights used in consensus operations for BC. Based on BC, several distributed detection and estimation problems in wireless sensor networks (WSN) were considered recently. In [94], distributed demodulation of space-time transmissions of a common message over a broadcast channel in WSN was dealt. The authors of [95], [96] considered the passive localization problem and proposed an expectation maximization-based distributed localization algorithm. A further work [97] considering the presence of outliers in WSN and developed a distributed passive localization scheme. To validate the performance of the distributed localization algorithms, the Cramér-Rao bound (CRB) of agent location was devised in [98], which shows that the distributed method can attain the CRB. In [99], the joint estimation of variable of interest and agent control framework was introduced, which demonstrates the intelligent behavior of the agents. The sensor registration problem was solved in [100] in a fully distributed manner. The authors of [101] investigated the events detection of cyber-physical systems based on BC by means of compressed sensing for applications such as attack detection, industrial process monitoring, etc. Also, a distributed Bernoulli filter was proposed in [102] which provides approximations of the Bayes-optimal estimates of the target presence probability to each sensor. Given the advantages of distributed processing, we can foresee the great potential in estimating the variables of interest in a distributed manner in B5G communications. This will enable the development of several promising applications in IVNs, as discussed above. To fully realize the advantages of exploiting distributed processing in solving the estimation and detection problems in B5G IVNs as discussed above, we aim for designing a generalized framework in this paper. The generalized framework is required to have sufficient flexibility and can be simply modified to fit various applications.

This paper provides a generalized estimation framework for the emerging IVNs in B5G. By constructing the state transition model and the measurement model, we formulate the generalized estimation and detection problem following the Bayes theorem. This centralized setup serves as a building block for the development of distributed approach. In particular, we apply the factor graph as a powerful tool to describe the relationship between the variables and the observations from different vehicles such that message passing algorithm can be implemented on the factor graph to determine the posterior distributions of the variables. Then, we switch our focus to a more robust and scalable distributed estimation framework for B5G. In an IVN without a fusion centre, all vehicles would cooperate and only share information with their neighbors such that the global estimate can be obtained at each vehicle locally.[2] The proposed framework exploits the BC algorithm that was originally proposed to fuse the local posteriors (beliefs) based on vehicles' individual observations. We mathematically prove that the the consensus can be accomplished by exchanging specific local metrics amongst the IVN. Then four different BC algorithms, namely, original consensus, metropolis consensus, gossip, and broadcast gossip algorithms are introduced and compared in terms of feasibility and performance. Considering the possibly high communication cost in terms of information exchange between vehicles, when performing V2V communications, we propose three approximate methods to simplify the local metric representation by only using a few parameters. Thus, only the parameters have to be exchanged and involved in the consensus operations. Moreover, we study two different cases, i.e., external target tracking and network decoding to illustrate the effectiveness of the proposed frameworks for IVNs. Besides, we have provided some discussions on how to modify the framework for addressing complex problems in the B5G IVNs. To sum up, our main contributions are as follows:

- We develop a generalized framework for estimating the variables of interests in IVNs of B5G.
- We introduce different consensus algorithms for obtaining the global estimate at each vehicles relying on single-hop V2V communications and local processing.
- To reduce the communication signaling overhead, we propose three approaches to approximate the local metrics. The tradeoff between approximation accuracy and communication overhead can be achieved.
- Two different problems in IVNs are studied and solved using the proposed distributed estimation framework. A sum product algorithm (SPA)-based consensus algorithm is further developed for network decoding.

[2]The global estimate denotes the estimation result based on all observations from the vehicles.

In the simulation results, we evaluate the target tracking performance and decoding performance based on the proposed estimation framework in terms of several indicators. Our results show that the performance of both target tracking and network decoding based on distributed estimation can approach that of the centralized method. We also show that the cooperation between vehicles can enhance the performance and improve the robustness to the presence of vehicle and RSU failures.

For ease of exposition, we summarize the list of acronyms and the list of notations in Tables 1 and 2, respectively. The remainder of this paper is organized as follows. We introduces the system model and some basic assumptions in Section II. In Section III, the generalized framework based on centralized and distributed processing is proposed. Two cases are then studied in Section IV to validate the proposed framework. Then the simulations results are shown and discussed in Section V. Finally, Section VI draws our conclusions.

II. SYSTEM MODEL

We consider a generic vehicular network, as shown in Fig. 3. The network consists of several road side units (RSUs) spaced at certain distances, serving multiple vehicles in its coverage. There are L vehicles in the network, labeled by $\mathcal{L} = \{1, 2, \ldots, L\}$. To establish communication links between the RSUs and the vehicles, both the RSUs and the vehicles are equipped with uniform linear arrays (ULA). For simplicity, we adopt the following basic assumptions:

Basic Assumptions:

1) The vehicles cruise straight along the road, i.e., they will not turn around.
2) The RSUs are connected with each other though optical fibres, enjoying unlimited fronthaul capacities to share information. In other words, all RSUs collaborate with each other to form a fusion center.
3) The communication channels between the RSUs and the vehicles are dominated by pure line-of-sight (LoS) propagation.

To support various applications in 5G and beyond, IVNs have to determine some variables of interest $\mathbf{x}_n = [x_{n,1}, \ldots, x_{n,J}]^{\mathrm{T}}$ at time instant n based on the observations at the vehicles.[3] Variable $x_{n,j}$, $\forall n \in \{1, \ldots, N\}$, $\forall j \in \{1, \ldots, J\}$, has a variety of meanings in IVN, such as the location of a specific target, the anomalous behavior in the networks, the message broadcasted in the network at time instant n. To construct the state model as well as the observation model, we make further assumptions as commonly adopted in the literature [103]:

A1) The states of vehicles and the variables of interest evolve according to a first-order Markov process [104].

[3]For the ease of expositions, all parameters and variables are assumed to be real numbers. The extension to complex space will be considered our future work.

TABLE 1 List of Acronyms

IVN	Intelligent Vehicular Nework
mMTC	Massive Machine-Type Communications
IoT	Internet-of-Things
V2V	Vehicle-to-Vehicle
QoS	Quality of Service
B5G	Beyond 5G (Fifth-Generation Wireless Systems)
RSU	Road Side Unit
OTFS	Orthogonal Time Frequency Space
OFDM	Orthogonal Frequency Division Multiplexing
NOMA	Nonorthogonal Multiple Access
OMA	Orthogonal Multiple Access
SIC	Successive Interference Cancelation
SINR	Signal-to-Interference-plus-Noise Ratio
FTN	Faster-than-Nyquist
AWGN	Additive White Gaussian Noise
CRB	Cramér-Rao Bound
BC	Belief Consensus
WSN	Wireless Sensor Netowrk
PF	Particle Filtering
ULA	Uniform Linear Array
LoS	Line-of-Sight
MMSE	Minimum Mean Square Error
BP	Belief Propagation
SPA	Sum Product Algorithm
pdf	Probability Distribution Function
LLF	Local Likelihood Function
ToA	Time-of-Arrival
AoA	Angle-of-Arrival
AP	Access Point
UAV	Unmanned Aerial Vehicle
BEC	Binary Erasure Channel
PSD	Power Spectral Density
LLR	Log-likelihood Ratio
RMSE	Root Mean Square Error
CDF	Cumulative Distribution Function
BER	Bit-Error-Rate
SNR	Signal-to-Noise Ratio
mmWave	Millimeter wave
DL	Deep Learning
DNN	Deep Neural Network

TABLE 2 List of Notations

$\mathbb{R}^n$	Real space of n dimensions
$\mathbb{B}^n$	Binary space of n dimensions
$\mathcal{S}^{(l)}$	Set of neighboring nodes of node l
$\lvert\mathcal{S}\rvert$	Cardinality of set $\mathcal{S}$
$\mathbb{E}_x(\cdot)$	Expectation of a function with respect to variable x
$\mathcal{L}$	Set of vehicle indices
$\mathcal{G}$	Communication graph of a network
$\max f$	The Maximum value of objective function f
$\mathrm{diag}[\mathbf{x}]$	Diagonal matrix with the main diagonal entries given by vector $\mathbf{x}$
L	Number of vehicles
N	Number of total time slots
D	Dimension of the vehicle state
J	Dimension of variables of interest
$(\cdot)^{\mathrm{T}}$	Transpose operator of an input matrix
$(\cdot)^{-1}$	Inverse operator of an input matrix
$\exp(\cdot)$	Exponent of an input function
$\delta(\cdot)$	Dirac delta function
∂	Partial derivative operator
$\propto$	Multiplicatively connected to a constant
$\odot$	Hadamard product
$\mathcal{O}$	An asymptotic notation describes the order of complexity
$\mathcal{N}(\mathbf{x};\mathbf{m_x},\mathbf{V_x})$	A Gaussian distribution of $\mathbf{x}$ with mean $\mathbf{m_x}$ and covariance matrix $\mathbf{V_x}$

A2) The states of different vehicles and variables $\mathbf{x}_n$ evolve independently, as described by their individual transition functions.

A3) At a single time instant, a vehicle can originate only one measurement and conversely, a measurement cannot originate from more than one vehicle.

A4) At time n, the measurements of different vehicles are conditionally independent with each other.

A5) Given the state of a vehicle $l \in \mathcal{L}$ and variables $\mathbf{x}_n$ at time n, the measurement obtained at vehicle l is conditionally independent from all its past measurements.

A. STATE EVOLUTION MODEL

As vehicles travel all the time, we denote the state of vehicle $l \in \mathcal{L}$ by vector $\mathbf{u}_n^{(l)} \in \mathbb{R}^D$, which may contain the position, the speed, and some other functional modes of vehicle l. By defining the state transition functions $f_n^{(l)}(\cdot) \in \mathbb{R}^D \to \mathbb{R}^D$ for the vehicles and $g_n(\cdot) \in \mathbb{R}^J \to \mathbb{R}^J$ for variables of interest, we have the state evolution model based on assumptions (A1) and (A2):

$$\mathbf{u}_n^{(l)} = f_n^{(l)}(\mathbf{u}_{n-1}^{(l)}), \tag{1}$$

$$\mathbf{x}_n = g_n(\mathbf{x}_{n-1}) + \mathbf{w}_n, \tag{2}$$

where $\mathbf{w}_n \in \mathbb{R}^J$ represent the noise in the Markov model, which is usually modeled as a multivariate Gaussian distributed random variable [46]. Remark that state $\mathbf{u}_n^{(l)}$ is perfectly known to vehicle l, whose transition is noise free. For brevity, we set $\mathbf{w}_n = \mathbf{w} \in \mathbb{R}^J, \forall n$, with zero mean and positive semi-definite covariance matrix $\mathbf{V_w} \in \mathbb{R}^{J\times J}$.

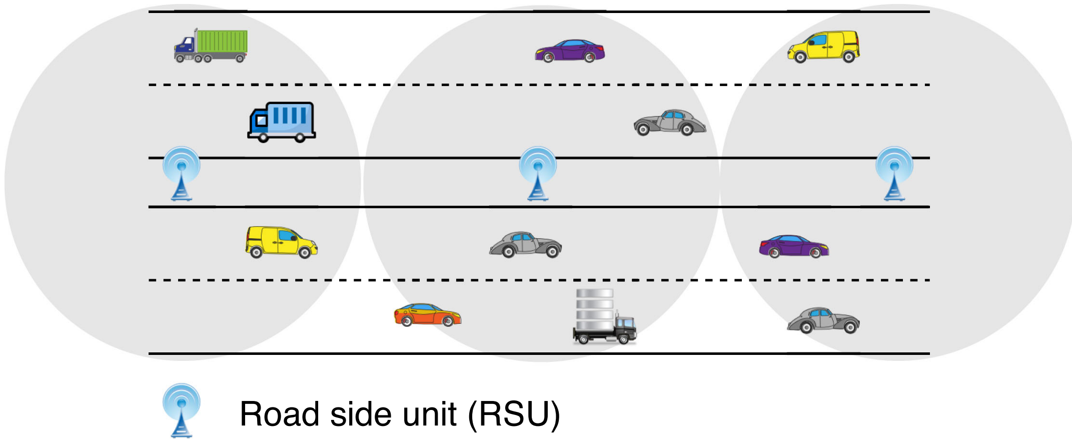


FIGURE 3. A vehicular network model which the area of coverage of the RSU is shaded in grey color.

B. OBSERVATION MODEL

After acquiring the data concerning the variables of interest, the observations are produced by detectors at the vehicles, following by some pre-processing algorithms of the raw data. Specifically, for vehicle $l \in \mathcal{L}$, its observation $\mathbf{r}_n^{(l)} \in \mathbb{R}^N$ concerning variables $\mathbf{x}_n$ at the nth time instant can be modeled as

$$\mathbf{r}_n^{(l)} = h_n^{(l)}(\mathbf{x}_n, \mathbf{u}_n^{(l)}) + \mathbf{z}_n^{(l)}, \tag{3}$$

where $h_n^{(l)}(\cdot) \in \mathbb{R}^J \times \mathbb{R}^D \rightarrow \mathbb{R}^N$ denotes the observation function and $\mathbf{z}_n^{(l)}$ represents the observation noise for vehicle l at time n. Similar to the state evolution model, we model $\mathbf{z}_n^{(l)}$ as a multivariate Gaussian variable with zero mean and positive semi-definite covariance matrix $\mathbf{V}_{\mathbf{z}_n^{(l)}} \in \mathbb{R}^{N\times N}$.

In the next section, we establish a general framework for IVNs based on the above state model and observation model. Then the estimation of variables of interest via centralized and distributed approaches will be introduced. As discussed in Section I, the centralized method has the advantages of simple implementation but not robust to the malfunctions of RSUs. The distributed method can tackle this problem by exchanging packets containing local information among the vehicles.

III. CENTRALIZED VS. DISTRIBUTION PROCESSING

A. GENERAL FRAMEWORK

Let $\mathbf{r}_n = [\mathbf{r}_n^{(1)}, \ldots, \mathbf{r}_n^{(L)}]^{\mathrm{T}}$ denote the observation of all L vehicles at time instant n and $\mathbf{r}_{1:n} \triangleq [\mathbf{r}_1^{\mathrm{T}}, \ldots, \mathbf{r}_n^{\mathrm{T}}]^{\mathrm{T}}$ be the stack of vectors of the observations of all vehicles up to time n. The estimates of the variables of interest at time n can therefore be obtained using the minimum mean square error (MMSE) estimator or the maximum *a posteriori* estimator [105]:

$$\text{MMSE: } \hat{\mathbf{x}}_n = \mathbb{E}\{\mathbf{x}_n|\mathbf{r}_{1:n}\} = \int \mathbf{x}_n p(\mathbf{x}_n|\mathbf{r}_{1:n})\mathrm{d}\mathbf{x}_n, \tag{4}$$

$$\text{MAP: } \hat{\mathbf{x}}_n = \arg\max_{\mathbf{x}_n} p(\mathbf{x}_n|\mathbf{r}_{1:n}), \tag{5}$$

where $p(\mathbf{x}_n|\mathbf{r}_{1:n})$ denotes the *a posteriori* distribution. According to the Bayes theorem [106], the current posterior $p(\mathbf{x}_n|\mathbf{y}_{1:n})$ can be rewritten as

$$p(\mathbf{x}_n|\mathbf{r}_{1:n}) = \frac{p(\mathbf{x}_n|\mathbf{r}_{1:n-1})p(\mathbf{r}_n|\mathbf{x}_n, \mathbf{r}_{1:n-1})}{p(\mathbf{r}_n|\mathbf{r}_{1:n-1})}, \tag{6}$$

where $p(\mathbf{x}_n|\mathbf{r}_{1:n-1})$, $p(\mathbf{r}_n|\mathbf{x}_n, \mathbf{r}_{1:n-1})$, and $p(\mathbf{y}_n|\mathbf{r}_{1:n-1})$ denotes the *a priori* distribution, the likelihood function and the normalization factor at time n, respectively. Following the assumptions in (A1) and (A5), $p(\mathbf{x}_n|\mathbf{r}_{1:n})$, $p(\mathbf{r}_n|\mathbf{x}_n, \mathbf{r}_{1:n-1})$, and $p(\mathbf{r}_n|\mathbf{r}_{1:n-1})$ can be simplified as

$$p(\mathbf{x}_n|\mathbf{r}_{1:n-1}) = p(\mathbf{x}_n), \tag{7}$$

$$p(\mathbf{r}_n|\mathbf{x}_n, \mathbf{r}_{1:n-1}) = p(\mathbf{r}_n|\mathbf{x}_n), \text{ and} \tag{8}$$

$$p(\mathbf{r}_n|\mathbf{r}_{1:n-1}) = p(\mathbf{r}_n), \tag{9}$$

respectively. Therefore, the posterior $p(\mathbf{x}_n|\mathbf{r}_{1:n}) = p(\mathbf{x}_n|\mathbf{r}_n)$. The likelihood function $p(\mathbf{r}_n|\mathbf{x}_n)$ can be further factorized into a product of several "local" likelihood functions (LLF) according to (A4), i.e.,

$$p(\mathbf{r}_n|\mathbf{x}_n) = \prod_{l=1}^{L} p(\mathbf{r}_n^{(l)}|\mathbf{x}_n). \tag{10}$$

Having the expression of observation model (3), the LLF $p(\mathbf{r}_n^{(L)}|\mathbf{x}_n)$ is expressed as

$$p(\mathbf{r}_n^{(l)}|\mathbf{x}_n) \propto \exp\left(-\frac{1}{2}\left(\mathbf{r}_n^{(l)} - h_n^{(l)}(\mathbf{x}_n, \mathbf{u}_n^{(l)})\right)^{\mathrm{T}} \times \mathbf{V}_{\mathbf{z}_n^{(l)}}^{-1}\left(\mathbf{r}_n^{(l)} - h_n^{(l)}(\mathbf{x}_n, \mathbf{u}_n^{(l)})\right)\right). \tag{11}$$

The current prior $p(\mathbf{x}_n)$ is obtained from the previous posterior and the state transition probability density function (pdf) in a sequential fashion as

$$p(\mathbf{x}_n) = p(\mathbf{x}_n|\mathbf{r}_{1:n-1}) = \int p(\mathbf{x}_n|\mathbf{x}_{n-1})p(\mathbf{x}_{n-1}|\mathbf{r}_{1:n-1})\mathrm{d}\mathbf{x}_{n-1}. \tag{12}$$

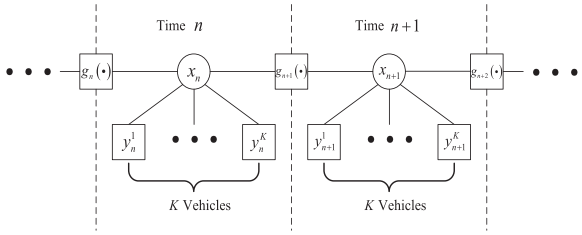


FIGURE 4. **A factor graph representing the factorization in (14). The shorthand notations g_n and $r_n^{(l)}$ are adopted to define the transition pdf $p(\mathbf{x}_n|\mathbf{x}_{n-1})$ and the likelihood function $p(\mathbf{r}_n^{(l)}|\mathbf{x}_n)$, respectively.**

Similar to (11), the state transition pdf is determined based on the state evolution model (2), given by

$$p(\mathbf{x}_n|\mathbf{x}_{n-1}) \propto \exp\left(-\frac{1}{2}\left(\mathbf{x}_n - g_n(\mathbf{x}_{n-1})\right)^{\mathrm{T}} \times \mathbf{V}_{\mathbf{w}}^{-1}\left(\mathbf{x}_n - g_n\left(\mathbf{x}_{n-1}\right)\right)\right). \tag{13}$$

In the next section, we will propose a centralized framework based factor graph and message passing algorithm to estimate the variables $\mathbf{x}_n$. Note that the performance of the following centralized approach serves as a benchmark for any distributed design. Besides, the structure of the centralized approach seems as a building bock for the development of the distributed approach.

B. CENTRALIZED APPROACH

In the centralized approach, the RSUs work as a fusion center for vehicular networks. After acquiring the observations, all vehicles send them back to the current home RSUs via uplink channels. Having collected all observations $\mathbf{y}_{1:n}$, the fusion center can factorize the posterior (6) which yields

$$\begin{aligned} p(\mathbf{x}_n|\mathbf{r}_n) &\propto p(\mathbf{x}_n)p(\mathbf{r}_n|\mathbf{x}_n) \\ &\propto \int p(\mathbf{x}_n|\mathbf{x}_{n-1})p(\mathbf{x}_{n-1}|\mathbf{r}_{1:n-1})\mathrm{d}\mathbf{x}_{n-1}\prod_{l=1}^{L} p(\mathbf{r}_n^{(l)}|\mathbf{x}_n) \\ &\propto \int p(\mathbf{x}_n|\mathbf{x}_{n-1})p(\mathbf{x}_{n-1})p(\mathbf{r}_{n-1}|\mathbf{x}_{n-1})\mathrm{d}\mathbf{x}_{n-1}\prod_{l=1}^{L} p(\mathbf{r}_n^{(l)}|\mathbf{x}_n) \\ &\propto \int p(\mathbf{x}_n|\mathbf{x}_{n-1})\cdots\int p(\mathbf{x}_1|\mathbf{x}_0)p(\mathbf{x}_0)\mathrm{d}\mathbf{x}_0 \\ &\quad \cdots p(\mathbf{r}_{n-1}|\mathbf{x}_{n-1})\mathrm{d}\mathbf{x}_{n-1}\prod_{l=1}^{L} p(\mathbf{r}_n^{(l)}|\mathbf{x}_n), \end{aligned} \tag{14}$$

where $p(\mathbf{x}_0)$ is the initial information available to the RSUs. In particular, the factorization in (14) can be represented by a factor graph, as shown in Fig. 4, where each variable node (denoted by a circle) represents a unique variable and each factor node (denoted by a square) represents a function.

On this factor graph, belief propagation (BP), also known as the sum-product algorithm (SPA), can be applied to compute the approximations of the posterior pdfs of the latent variables, i.e., $b(\mathbf{x}_n) \approx p(\mathbf{x}_n|\mathbf{r}_{1:n})$. As a popular solution, BP defines two kind of messages on a factor graph, i.e., the message from factor node f to variable node x,

$$\mu_{f\to x}(x) = \int f(\mathbf{x}) \prod_{x'\in\mathcal{S}_f\backslash x} \mu_{x'\to f}(x')\mathrm{d}x,' \tag{15}$$

and the message from variable node x to factor node f,

$$\mu_{x\to f}(x) = \prod_{f'\in\mathcal{S}_x\backslash f} \mu_{f'\to x}(x), \tag{16}$$

where $\mathcal{S}_x$ and $\mathcal{S}_f$ denote the sets of all functions containing variable x and all variables in function f, respectively. The approximate posterior pdf is determined by the product of messages coming from all connected factor nodes, which can be expressed as

$$b(x) = \prod_{f\in\mathcal{S}_x} \mu_{f\to x}(x). \tag{17}$$

After running BP on the factor graph, the MMSE estimates of $\mathbf{x}_n$ is given by $\hat{\mathbf{x}}_n = \mathbb{E}_{b(\mathbf{x}_n)}[\mathbf{x}_n]$. Since the observations of all vehicles are only available at the fusion centre, all messages are calculated at the RSUs, resulting a centralized estimation approach. Although the centralized method can achieve the best performance in terms of estimation results and most computations are performed at the fusion center, it does not suit for the emerging IVNs for B5G communication systems. In the next section, we will propose a distributed estimation framework for IVNs.

C. DISTRIBUTED APPROACH

We commence from a vehicular network that RSUs are not working well in the considered network and hence there is no fusion centre available to collect all the global observations. In B5G IVNs, it is expected that vehicles should have the capability of sensing the environments to avoid possible collisions and satisfy other autonomous vehicle features [107]. Without a fusion centre, vehicle l can only obtain the posterior $p(\mathbf{x}_n|\mathbf{r}_n^{(l)})$ based on its local observations, leading to some ambiguities in the estimation results of $\mathbf{x}_n$. To this end, we propose a distributed estimation framework, through which all vehicles can accurately estimate the variables of interest as if all observations have been collected.

To facilitate distributed estimation in B5G network, efficient communication between vehicles are of utmost importance. The network topology at time instant n can be described by graph $\mathcal{G}_n$ as shown in Fig. 5, where each vertex represents a vehicle. Relying on appropriate communication technologies, a vehicle can communicate with other vehicles within its range of communication. In the figure, two vehicles are connected by an edge if and only if they can communicate with each other. The set of all neighboring vertices connected to vertex l is defined as $\mathcal{S}_n^{(l)}$. We say that graph $\mathcal{G}_n$ is connected if any set $\mathcal{S}_n^{(l)}, \forall l \in \mathcal{L}$, has at least one element. The node degree (the number of neighboring vehicles) of vehicle l at time n is defined by $|\mathcal{S}_n^{(l)}|$. The connectivity of a graph $\mathcal{G}_n$ is captured by

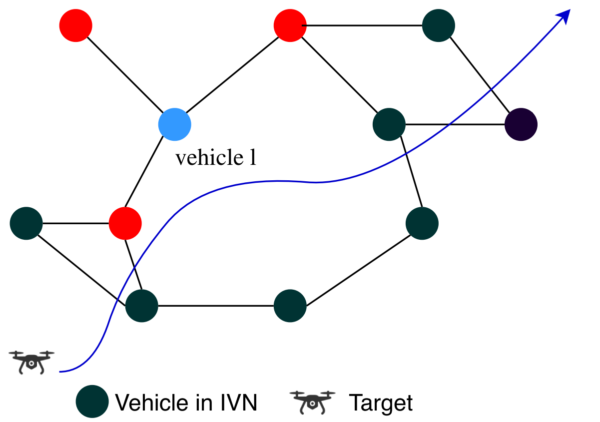


FIGURE 5. A network topology of the IVN. A solid line between two vehicle nodes denote the communication link between them. For vehicle l marked with blue color, the set $\mathcal{S}_n^{(l)}$ consists of the three connected vehicle marked with red color.

a binary adjacent matrix $\mathbf{A}$, where its element $A_{lm} = A_{ml} = 1$ if vehicle l and vehicle m can communicate with each other. For simplicity, the communication links between the vehicles are assumed to be noise free in what follows.

At time instant n, vehicle l formulates its LLF $p(\mathbf{r}_n^{(l)}|\mathbf{x}_n)$ and local posterior $p(\mathbf{x}_n|\mathbf{r}_n^{(l)})$ based on its observations. Then, the distributed process can be defined by reaching consensus on the (joint) *a posteriori* distribution over the IVN [82], i.e,

$$\mathrm{BC}\{p(\mathbf{x}_n|\mathbf{r}_n^{(1)}), \ldots, p(\mathbf{x}_n|\mathbf{r}_n^{(L)})\} = p(\mathbf{x}_n|\mathbf{r}_n). \tag{18}$$

Remark that the prior at time n is known and is identical to all vehicles, thus the above problem can be simplified as

$$\mathrm{BC}\{p(\mathbf{r}_n^{(1)}|\mathbf{x}_n), \ldots, p(\mathbf{r}_n^{(L)}|\mathbf{x}_n)\} = \prod_{l=1}^{L} p(\mathbf{r}_n^{(l)}|\mathbf{x}_n) = p(\mathbf{r}_n|\mathbf{x}_n). \tag{19}$$

Applying the expression of the LLF (11), the joint likelihood function $p(\mathbf{r}_n|\mathbf{x}_n)$ can be written as[4]

$$\begin{aligned}
&p(\mathbf{r}_n|\mathbf{x}_n)\\
&\propto \exp\left(-\frac{1}{2}\sum_{l=1}^{L}\left(\mathbf{r}_n^{(l)} - h_n^{(l)}(\mathbf{x}_n)\right)^{\mathrm{T}} \mathbf{V}_{\mathbf{z}_n^{(l)}}^{-1}\left(\mathbf{r}_n^{(l)} - h_n^{(l)}(\mathbf{x}_n)\right)\right)\\
&\propto \exp\left(\frac{1}{2}\left[\sum_{l=1}^{L}\left[\mathbf{r}_n^{(l)}\right]^{\mathrm{T}} \mathbf{V}_{\mathbf{z}_n^{(l)}}^{-1} h_n^{(l)}(\mathbf{x}_n) + \left[h_n^{(l)}(\mathbf{x}_n)\right]^{\mathrm{T}} \mathbf{V}_{\mathbf{z}_n^{(l)}}^{-1}\right.\right.\\
&\qquad\left.\left.\times\left(\mathbf{r}_n^{(l)} - h_n^{(l)}(\mathbf{x}_n)\right)\right]\right)\\
&\propto \exp\left(\sum_{l=1}^{L}\underbrace{\left[h_n^{(l)}(\mathbf{x}_n)\right]^{\mathrm{T}} \mathbf{V}_{\mathbf{z}_n^{(l)}}^{-1}\left(\mathbf{r}_n^{(l)} - \frac{1}{2}h_n^{(l)}(\mathbf{x}_n)\right)}_{L(\mathbf{r}_n^{(l)}, \mathbf{x}_n)}\right),
\end{aligned} \tag{20}$$

where $L(\mathbf{r}_n^{(l)}, \mathbf{x}_n)$ defines a local statistic metric. We further define the global metric $L(\mathbf{r}_n, \mathbf{x}_n)$ as

$$L(\mathbf{r}_n, \mathbf{x}_n) = \sum_{l=1}^{L} L(\mathbf{r}_n^{(l)}, \mathbf{x}_n). \tag{21}$$

Since $L(\mathbf{r}_n, \mathbf{x}_n)$ can fully describe the joint likelihood function, the vehicles need to have the knowledge of the global metric $L(\mathbf{r}_n, \mathbf{x}_n)$ to address the target tracking problem in IVN. This is enabled by establishing communication links between the neighboring vehicles and local computations. Next, we will introduce the implementation of four consensus algorithms to obtain the global metric at all vehicles in a distributed manner. The pros and cons for different consensus algorithms will also be stated.

1) ORIGINAL CONSENSUS

The consensus operations are simultaneously performed at all vehicles and each vehicle will update its local metric iteratively based on the received information from its neighboring vehicles. At the very beginning, the local metrics for vehicle $l \in \mathcal{L}$ are initialized as $L_n^{(l)}(0) = L(\mathbf{r}_n^{(l)}, \mathbf{x}_n)$. Then at the tth iteration of the consensus algorithm, the local metric is updated as [108]

$$\begin{aligned}
L_n^{(l)}(t) &= L_n^{(l)}(t-1) + \xi \sum_{l' \in \mathcal{S}_n^{(l)}} \left(L_n^{(l')}(t-1) - L_n^{(l)}(t-1)\right)\\
&= \left(1 - \xi|\mathcal{S}_n^{(l)}|\right) L_n^{(l)}(t-1) + \xi \sum_{l' \in \mathcal{S}_n^{(l)}} L_n^{(l')}(t-1),
\end{aligned} \tag{22}$$

where $L_n^{(l)}(t-1)$ is the local metric of vehicle l obtained from the previous iteration and ξ denotes the update weight. The consensus operation (22) can be regarded as a process of merging information from the vehicle itself and from its neighboring vehicles. A general choice of the rate ξ is $1/\gamma_n$, where $\gamma_n = \max_l |\mathcal{S}_n^{(l)}|$ indicates the maximum node degrees of graph $\mathcal{G}_n$. If graph $\mathcal{G}_n$ is connected, the local metrics of all vehicles are guaranteed to converge when the number of consensus iterations approaches infinity, i.e., $\lim_{t\to+\infty} L_n^{(l)}(t) = \frac{L(\mathbf{r}_n, \mathbf{x}_n)}{L}$ [87]. In practice, running a few iterations N_{iter} is able to provide a sufficiently accurate approximation of the actual one. Then the global metric $L(\mathbf{r}_n, \mathbf{x}_n)$ as well as the joint likelihood function $p(\mathbf{r}_n|\mathbf{x}_n)$ can be easily found.

$$\begin{aligned}
&L_n^{(l)}(t)\\
&= \begin{cases}
\left(1 - \xi|\mathcal{S}_n^{(l)}|\right) L_n^{(l)}(t-1) + \xi \sum_{l' \in \mathcal{S}_n^{(l)}} L_n^{(l')}(t-1), \\
\left(1 - \xi|\mathcal{S}_n^{(l)}|\right) L_n^{(l)}(t-1) \qquad\qquad \text{if link failure} \\
+\xi \left(\sum_{l' \in \mathcal{S}_n^{(l)} \setminus m} L_n^{(l')}(t-1) + L_n^{(l')}(t-2)\right)
\end{cases}
\end{aligned} \tag{23}$$

Remark 1: The link failures between connected vehicles can be addressed by using the following scheme.

[4]For brevity, we omit the known vehicle states $\mathbf{u}_n^{(l)}$ in equation (20).

As the vehicles in the IVN are dynamic, link failure may happen to two vehicles even if they are within the communication range, due to unexpected obstacles or signal detection failures. In this circumstance, vehicle l can use an auxiliary metric $L_n^{(l,m)}$ to store the local metric from neighboring vehicle $m \in \mathcal{S}_n^{(l)}$ obtained in the previous iteration. For instance, at the $t-1$th consensus iteration, vehicle l records the local metric $L_n^{(m)}(t-2)$ as $L_n^{(l,m)}$. Then if the link between vehicles l and m fails in the tth iteration, vehicle l can adopt the auxiliary metric to update $L_n^{(l)}(t)$. Based on this protocol, the consensus operations are modified as (23) at the bottom of this page. The second line on the right hand side of (23) can be seen as an approximation of the first line by using the stored metric $L_n^{(l')}(t-2)$ to replace the actual one $L_n^{(l')}(t-1)$ that is not available. On the other hand, by adopting the above protocol, the vehicles can update their local metrics without waiting for all information from their neighbors to arrive. Therefore, employing (23) can relax the synchronization requirement for distributed estimation in IVNs.

2) METROPOLIS CONSENSUS

Existing researches show that sharing the same update weight ξ for all vehicles may lead to performance loss [86]. To tackle this problem, we introduce the metropolis weight defined in [86], which provides a better convergence behavior. With the same initializations, the local metric in metropolis consensus is given by

$$L_n^{(l)}(t) = \xi^{(l,l)} L_n^{(l)}(t-1) + \sum_{l' \in \mathcal{S}_n^{(l)}} \xi^{(l,l')} L_n^{(l')}(t-1), \quad (24)$$

with the weight $\xi^{(l,l')}$ expressed as

$$\xi^{(l,l')} = \xi^{(l,'l)} = \begin{cases} 1/\max\left[\left|\mathcal{S}_n^{(l)}\right|, \left|\mathcal{S}_n^{(l')}\right|\right], & \text{for } l \neq l,' \\ 1 - \sum_{m \in \mathcal{S}_n^{(l)}} \xi^{(m,l)}, & \text{for } l = l'. \end{cases} \quad (25)$$

Note that in the original consensus algorithm (22), all vehicles need to know the maximum degrees of graph $\mathcal{G}_n$ to determine the weight ξ. While in the metropolis consensus algorithm, the vehicles only require the degree information of their neighbors. Therefore, implementing metropolis consensus is more attractive for the realization of distributed estimation in IVN.

3) GOSSIP

In contrast to the consensus algorithms using constant and metropolis weights, gossip-based algorithms [109] can also be used for distributed estimation without the prior knowledge of the node degrees of the graph. At the t-th consensus iteration, vehicle l exchanges its local metric with a randomly chosen neighboring vehicle $l' \in \mathcal{S}_n^{(l)}$ and update their local metrics as follows:

$$L_n^{(l)}(t) = L_n^{(l')}(t) = \frac{1}{2}\left(L_n^{(l)}(t-1) + L_n^{(l')}(t-1)\right), \quad (26)$$

while all other vehicles does not perform update at this iteration. Since only two local metrics are updated in each iteration, the total required number of consensus iterations for updating all vehicles is $\frac{N_{\text{iter}} L}{2}$, which introduces excessive latency for large-scale IVNs compared to the that of the consensus algorithm.

4) BROADCAST GOSSIP

Naturally, the exceedingly high latency is not preferred due to the dynamic nature of the IVNs. As a result, the so-called broadcast gossip algorithm is proposed to tackle this issue [110], following which the local metrics are updated as

$$L_n^{(l')}(t) = \begin{cases} \eta L_n^{(l')}(t-1) + (1-\eta) L_n^{(l)}(t-1), & l' \in \mathcal{S}_n^{(l)} \\ L_n^{(l')}(t-1), & \text{otherwise}, \end{cases} \quad (27)$$

where $0 < \eta < 1$ is the update rate. The optimal value of η has been discussed in [110], which is related to the algebraic connectivity of graph $\mathcal{G}_n$. Since it is usually very difficult to obtain algebraic connectivity without a fusion centre, parameter η is chosen based on some empirical studies. Note that in the gossip-based consensus algorithms, the updating of local metrics follows a random manner. However, it was proved in [110] that this kind of random updating cannot guarantee the convergence to the global metric in general. In Table 3, we compare the four consensus algorithms in terms of several features. In the following, we will discuss some practical issues in the implementation of the above algorithms.

Approximation for the Local Metrics: Employing the consensus algorithms above allow all vehicles to obtain the estimates of $\mathbf{x}_n$ distributively. However, the observation function $h_n^{(l)}(\mathbf{x}_n)$ is in general not a linear function, so are the local metrics $L(\mathbf{r}_n^{(l)}, \mathbf{x}_n)$. As the vehicles are not able to transmit the continuous functions $L(\mathbf{r}_n^{(l)}, \mathbf{x}_n)$ through the network, sampling-based methods are used to approximate the local metrics. A direct but inefficient solution is to represent $L_n^{(l)}(t)$ on a grid in the state space of $\mathbf{x}_n$. Another way to handle the nonlinearity of the observation function is via particle filtering, which adopts a set of randomly generated particles $\{\mathbf{x}_n^{[p]}\}_{p=1}^P$ and corresponding weights $\{\omega_n^{[p],(l)}\}_{p=1}^P$ to approximate the nonlinear function, where P denotes the number of particles [111]. As a result, the local metric is therefore represented by

$$L(\mathbf{r}_n^{(l)}, \mathbf{x}_n) \approx \sum_{p=1}^{P} \omega_n^{[p],(l)} \delta(\mathbf{x}_n^{[p]} - \mathbf{x}_n). \quad (28)$$

At each time instant, the same particles are randomly drawn for all vehicles and the weights are calculated individually based on the local metrics. Then the consensus operations are executed to reach the agreement on the local weights of connected vehicles. After N_{iter} consensus iterations, all local weights $\omega_n^{[p],(l)}$, $\forall l \in \mathcal{L}$, converge to the global weights

TABLE 3 Comparison of Different Consensus Algorithms

Algorithm	No. iterations	Converge to global metric	Known neighbors' degrees	Known max. degree
Original consensus	N_{iter}	Yes	Yes	Yes
Metropolis consensus	N_{iter}	Yes	Yes	No
Gossip	$\lceil L \cdot N_{\text{iter}} \rceil /2$	No	No	No
Broadcast Gossip	N_{iter}	No	No	No

$\omega_n^{[p],(l)}(N_{\text{iter}}) \approx \omega_n^{[p]}$ such that

$$L(\mathbf{r}_n, \mathbf{x}_n) \approx \sum_{p=1}^{P} \omega_n^{[p],(l)}(N_{\text{iter}}) \delta(\mathbf{x}_n^{[p]} - \mathbf{x}_n). \tag{29}$$

The accuracy of PF based approximation depends on the number of particles employed. To achieve good estimation result, we have to choose a large value of P, requiring a communication overhead of $\mathcal{O}(P)$.

For the purpose of reducing communication overhead, we can employ appropriate approximations for the nonlinear function $h_n^{(l)}(\mathbf{x}_n)$, such that the local metric can be represented by a fewer number of parameters. For example, provided a series of orthonormal basis functions $\{\phi_{n,q}(\mathbf{x}_n)\}_{q=1}^{Q}$ for an inner product space, the projection of the local metric $h_n^{(l)}(\mathbf{x}_n)$ onto $\{\phi_{n,q}(\mathbf{x}_n)\}_{q=1}^{Q}$ can be represented as $L_n^{(l)}(t)$

$$h_n^{(l)}(\mathbf{x}_n) = \sum_{q=1}^{Q} \omega_{n,q}^{(l)} \phi_{n,q}(\mathbf{x}_n), \tag{30}$$

where Q is the dimension of the basis functions. The coefficient $\omega_{n,q}^{(l)}$ is determined by

$$\omega_{n,q}^{(l)} = \int h_n^{(l)}(\mathbf{x}_n) \phi_{n,q}(\mathbf{x}_n) \mathrm{d}\mathbf{x}_n. \tag{31}$$

Note that for different vehicles, we can adopt the same basis functions. Therefore the consensus of vehicles can be reached by sharing and updating the coefficient $\omega_{n,q}^{(l)}$, having a communication overhead of $\mathcal{O}(Q)$.

Alternatively, we can further reduce the communication overhead by leveraging the powerful Taylor series expansion of $h_n^{(l)}(\mathbf{x}_n)$, i.e.,

$$\begin{aligned} h_n^{(l)}(\mathbf{x}_n) &= h_n^{(l)}(\mathbf{a}) + \sum_{j=1}^{J} \frac{\partial h_n^{(l)}(\mathbf{a})}{\partial x_{n,j}} \left(x_{n,j} - a_j\right) \\ &+ \frac{1}{2!} \sum_{i,j=1}^{J} \frac{\partial^2 h_n^{(l)}(\mathbf{a})}{\partial x_{n,j} \partial x_{n,i}} \left(x_{n,j} - a_j\right)\left(x_{n,i} - a_i\right) \ldots + \Delta_p, \end{aligned} \tag{32}$$

where $\mathbf{a} = [a_1, \ldots, a_J]^{\mathrm{T}}$ is the reference point for expansion that $h_n^{(l)}(\mathbf{x}_n)$ is differentiable at $\mathbf{x}_n = \mathbf{a}$ and Δ_p is the Peano form of the remainder [112]. The reference point $\mathbf{a}$ can be chosen according to the prior $p(\mathbf{x}_n)$ obtained from the state evolution model. Using the first order Taylor series expansion for $h_n^{(l)}(\mathbf{x}_n) = \mathbf{A}\mathbf{x}_n + \mathbf{b}$, the local metric $L(\mathbf{r}_n^{(l)}, \mathbf{x}_n)$ is expressed as

$$L(\mathbf{r}_n^{(l)}, \mathbf{x}_n) = -\frac{1}{2} \mathbf{x}_n^{\mathrm{T}} \mathbf{A}^{\mathrm{T}} \mathbf{V}_{\mathbf{z}_n^{(l)}}^{-1} \mathbf{A}\mathbf{x}_n + \left[\mathbf{r}_n^{(l)}\right]^{\mathrm{T}} \mathbf{V}_{\mathbf{z}_n^{(l)}}^{-1} \mathbf{A}\mathbf{x}_n, \tag{33}$$

which is in a quadratic form with respect to $\mathbf{x}_n$. Consequently, the LLF is Gaussian distributed whose mean and variance are broadcasted for consensus operations, resulting in a communication overhead of $\mathcal{O}(2)$. Although applying Taylor expansion to simplify the observation functions leads to a very low communication cost, the choice of the reference points has a significant impact on the estimation performance [46]. Obviously, the communication cost of the distributed method is dominated by the number of parameters to represent the local metrics. The above three approximations have varying communication overheads and performance. In practical scenarios, we may combine different approximate methods to achieve a good tradeoff between the communication cost and estimation performance.

In the above, we have shown a general distributed estimation framework for B5G IVNs. In the following section, we will study two different cases in IVNs to evaluate the efficiency of the proposed framework.

IV. CASE STUDY

In this section, two cases based on the proposed distributed estimation framework in IVNs will be considered. Specifically, we will study the target tracking problem and the cooperative network decoding problem, respectively.

A. CASE I: TARGET TRACKING

The location awareness of targets plays an important role for IVNs in B5G to support applications such as emergence rescue and traffic safety [113]. In the target tracking scenario, we aim for obtaining real time locations of some external targets. For simplicity, we assume that the vehicles are capable of separating the signals from different targets based on data association methods, e.g., [103]. Therefore, we can focus on one target, i.e., the variable of interest $\mathbf{x}_n = [x_n, y_n]^{\mathrm{T}}$, where x_n and y_n denotes the coordinates of the target on x-axis and y-axis. The problem becomes the estimation of target coordinates at time instant n, i.e.,

$$\{\hat{x}_n, \hat{y}_n\} = \int\int x_n y_n p(x_n, y_n | \mathbf{r}_{1:n}) \mathrm{d}x_n \mathrm{d}y_n. \tag{34}$$

In this case, we consider at time instant n, vehicle l can acquire the time-of-arrival (ToA) measurement $\tau_n^{(l)}$ from the signal delay and the angle-of-arrival (AoA) measurement $\theta_n^{(l)}$

from the directional beam of the ULA.[5] The state variable $\mathbf{u}_n^{(l)} = [u_{x,n}^{(l)}, u_{y,n}^{(l)}]^{\mathrm{T}}$ denotes the location of vehicle l at time n. Thus, the observation $\mathbf{r}_n^{(l)}$ can be written as

$$\mathbf{r}_n^{(l)} = \begin{bmatrix} r_{x,n}^{(l)} \\ r_{y,n}^{(l)} \end{bmatrix} = \begin{bmatrix} c\tau_n^{(l)} \cos\theta_n^{(l)} \\ c\tau_n^{(l)} \sin\theta_n^{(l)} \end{bmatrix} + \mathbf{z}_n^{(l)}$$
$$= \begin{bmatrix} x_n - u_{x,n}^{(l)} \\ y_n - u_{y,n}^{(l)} \end{bmatrix} + \begin{bmatrix} z_{x,n}^{(l)} \\ z_{y,n}^{(l)} \end{bmatrix}, \quad (35)$$

where $r_{x,n}^{(l)}$ and $r_{y,n}^{(l)}$ are the relative distances on x-axis and y-axis of vehicle l at time n, respectively, with the signal propagation speed c. Without loss of generality, the observation noise on x-axis and y-axis obeys the same Gaussian distribution with zero mean and variance $v_{z_n^{(l)}}$. According to the log-distance path loss model [114], the observation variance is related to the distance from the target to the vehicle. Under the assumption of unit signal energy and a free space path loss exponent of 2, the noise power $v_{z_n^{(l)}}$ is given by

$$v_{z_n^{(l)}} = v_0 \cdot \left(\frac{c\tau_n^{(l)}}{d_0} \right)^2, \quad (36)$$

where $d_0 = 10$ m is the reference distance from the target and v_0 denotes the observation noise power at d_0.

Next, we study the state evolution model for $\mathbf{x}_n$, which can be formulated as[6]

$$\mathbf{x}_n = \mathbf{x}_{n-1} + \mathbf{s}_n \cdot \delta_t + \mathbf{w}$$
$$= \begin{bmatrix} x_{n-1} \\ y_{n-1} \end{bmatrix} + \delta_t \cdot \begin{bmatrix} s_{x,n} \\ s_{y,n} \end{bmatrix} + \begin{bmatrix} w_x \\ w_y \end{bmatrix}, \quad (37)$$

where $\mathbf{s}_n = [s_{x,n}, s_{y,n}]^{\mathrm{T}}$ denotes the velocity of the target and δ_t is the duration of a time slot. Similar to the observation noise $\mathbf{z}$, the transition noise w_x and w_y are modeled by zero mean Gaussian variables with variance v_w. As the external target is usually non-cooperative, its velocity is not available. To handle this, we approximate the velocity by

$$\hat{s}_n = \frac{\hat{\mathbf{x}}_{n-1} - \hat{\mathbf{x}}_{n-2}}{\delta_t}, \quad (38)$$

where $\hat{\mathbf{x}}_{n-1}$ and $\hat{\mathbf{x}}_{n-2}$ are the estimated target location of the previous two time instants. According to the observation and the state models, the x and y-coordinates are updated independently and the corresponding variable nodes are split into two subgraphs, as shown in Fig. 6.

For simplicity, we focus on the message passing related to x-coordinate. The messages concerning y-coordinate can be obtained in a similar way using the factor graph model and BP rules. Assuming that the belief x_{n-1} is available in a Gaussian form as $b(x_{n-1}) = \mathcal{N}(x_{n-1}; m_{x_{n-1}}, v_{x_{n-1}})$, the message from g_n to x_n can be derived according to (15),

$$\mu_{g_n \to x_n}(x_n) \propto \int \exp\left(-\frac{(x_n - x_{n-1} - \hat{s}_{x,n}\delta_t)^2}{2v_w} \right) \cdot \exp\left(-\frac{(x_{n-1} - m_{x_{n-1}})^2}{2v_{x_{n-1}}} \right) \mathrm{d}x_{n-1}$$
$$\propto \mathcal{N}\left(x_n; m_{g_n \to x_n}, v_{g_n \to x_n}\right), \quad (39)$$

with the corresponding mean and variance given by

$$m_{g_n \to x_n} = m_{x_{n-1}} + \hat{s}_{x,n}\delta_t, \text{ and} \quad (40)$$
$$v_{g_n \to x_n} = v_{x_{n-1}} + v_w, \quad (41)$$

respectively. The message from $r_{x,n}^{(l)}$ to x_n is identical to the likelihood function $p(r_{x,n}^{(l)}|x_n)$, given by

$$\mu_{r_{x,n}^{(l)} \to x_n}(x_n) = p(r_{x,n}^{(l)}|x_n)$$
$$\propto \exp\left(-\frac{\left(r_{x,n}^{(l)} - (x_n - u_{x,n}^{(l)})\right)^2}{2v_{z_n^{(l)}}} \right)$$
$$\propto \mathcal{N}\left(x_n; r_{x,n}^{(l)} + u_{x,n}^{(l)}, v_{z_n^{(l)}}\right). \quad (42)$$

Then the belief of x_n can be determined according to (17), which is still a Gaussian distribution with mean m_{x_n} and variance v_{x_n}, given by

$$m_{x_n} = v_{x_n} \cdot \left(\frac{m_{x_{n-1}} + \hat{s}_{x,n}\delta_t}{v_{x_{n-1}} + v_w} + \sum_{l=1}^{L} \frac{r_{x,n}^{(l)} + u_{x,n}^{(l)}}{v_{z_n^{(l)}}} \right), \quad (43)$$

$$v_{x_n} = \left(\frac{1}{v_{x_{n-1}} + v_w} + \sum_{l=1}^{L} \frac{1}{v_{z_n^{(l)}}} \right)^{-1}, \quad (44)$$

respectively. It can be seen from (43) and (44) that the estimated mean and variance corresponding to the target at time n

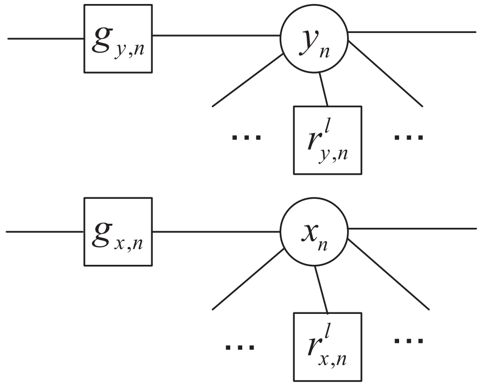


FIGURE 6. **A modified factor graph for target tracking. The factor nodes $g_{x,n}$ and $g_{y,n}$ denote the nth state transition function for x and y coordinates, and $r_{x,n}^{(l)}$ and $r_{y,n}^{(l)}$ denote the likelihood function $p(r_{x,n}^l|x_n)$ and $p(r_{y,n}^l|y_n)$, respectively.**

[5]The target can be tracked solely based on ToA or AoA measurements by solving nonlinear functions. Since our main scope is to design a generalized framework, a linearized model based on ToA and AoA measurements is considered here.

[6]Here, we impose an assumption that the velocity of the target remains constant in a short time period δ_t.

consist of the prior information derived from the state evolution model as well as the information obtained from vehicles' observations. Following a similar process, the belief of y_n is derived with mean m_{y_n} and variance v_{x_n}. Then the location estimate of the target at time n is given by MMSE estimation, i.e., $\hat{\mathbf{x}}_n = [m_{x_n}, m_{y_n}]^{\mathrm{T}}$.

Next, we consider the distributed calculation of the target location using our proposed framework in Section III. Based on the likelihood function $p(r_{x,n}^{(l)}|x_n)$, we can define the local metric of vehicle l as

$$L(r_{x,n}^{(l)}, x_n) = -\frac{1}{2v_{z_n^{(l)}}}x_n^2 + x_n \cdot \frac{\left(r_{x,n}^{(l)} + u_{x,n}^{(l)}\right)}{z_n^{(l)}}, \tag{45}$$

which is parameterized by $\lambda_n^{(l)} = \frac{1}{2v_{z_n^{(l)}}}$ and $\mu_n^{(l)} \frac{(r_{x,n}^{(l)}+u_{x,n}^{(l)})}{z_n^{(l)}}$. With the initialization $\mu_n^{(l)}(0) = \mu_n^{(l)}$ and $\lambda_n^{(l)}(0) = \lambda_n^{(l)}$, the consensus operation with metropolis weight is given by

$$\mu_n^{(l)}(t) = \xi^{(l,l)}\mu_n^{(l)}(t-1) + \sum_{l' \in \mathcal{S}_n^{(l)}} \xi^{(l,l')}\mu_n^{(l')}(t-1), \tag{46}$$

$$\lambda_n^{(l)}(t) = \xi^{(l,l)}\lambda_n^{(l)}(t-1) + \sum_{l' \in \mathcal{S}_n^{(l)}} \xi^{(l,l')}\lambda_n^{(l')}(t-1). \tag{47}$$

After running N_{iter} iterations, all vehicles have $\mu_n^{(l)}(N_{\text{iter}}) \approx \sum_{l \in \mathcal{L}} \mu_n^{(l)}/L$ and $\lambda_n^{(l)}(N_{\text{iter}}) \approx \sum_{l \in \mathcal{L}} \lambda_n^{(l)}/L$ and the global metric is written by

$$L(\mathbf{r}_{x,n}, x_n) = -L\lambda_n^{(l)}(N_{\text{iter}}) \cdot x_n^2 + L\mu_n^{(l)}(N_{\text{iter}}) \cdot x_n. \tag{48}$$

Consequently, the belief of x_n is given by

$$\begin{aligned} b(x_n) &\propto \exp\left(-\frac{(x_n - m_{g_n \to x_n})^2}{2v_{g_n \to x_n}}\right) \exp\left(L(\mathbf{r}_{x,n}, x_n)\right) \\ &\propto \mathcal{N}(x_n; m_{x_n}, v_{x_n}), \end{aligned} \tag{49}$$

with

$$m_{x_n} = v_{x_n}\left(\frac{m_{g_n \to x_n}}{m_{g_n \to x_n}} + L\mu_n^{(l)}(N_{\text{iter}})\right), \tag{50}$$

$$v_{x_n} = \left(\frac{1}{v_{g_n \to x_n}} + L\lambda_n^{(l)}(N_{\text{iter}})\right)^{-1}. \tag{51}$$

Note that the calculation of the belief is done locally as the global metric can be determined based on the local metric of any vehicle $l \in \mathcal{L}$. Based on our discussions concerting (43) and (44), the distributed estimation of m_{x_n} and v_{x_n} also depends on the prior information and the observation-based information from all vehicles. Since all vehicles have reached consensus on the global likelihood function, using L times of the local parameters is equivalent to collecting observations from all vehicles. The consensus operations are performed for y_n similar to x_n, and finally, all vehicles obtain the estimate of the target location at time n in a distributed fashion, despite the absent of a centralized fusion centre.

B. CASE II: NETWORK DECODING

In some special scenarios in IVNs for B5G, there exist a moving access point (AP, such as unmanned aerial vehicle (UAV) etc. [115]–[117]) which broadcasts an important message to the vehicles, i.e., severe traffic accidents, extreme weather conditions. Due to conceivably low signal-to-noise ratio (SNR) conditions, each vehicle may be not able to decode the broadcasted message reliably relying on the individual observation [94]. Assuming that at time instant n, the AP broadcasts message $\mathbf{x}_n$ to the IVN. For simplicity, the transmitted message is a binary vector of length J, i.e., $x_{n,j} \in \{0, 1\}$, $1 \leq j \leq J$. We assume that the channels from the AP to the vehicles are memoryless and independent for different vehicles. Different from the target tracking problem where the target location is a continuous random variable, using the MMSE estimation for discrete random variables is generally suboptimal. Therefore, we consider the MAP estimator in (5) that the estimate of the message is given by

$$\hat{\mathbf{x}}_n = \arg \max_{\mathbf{x}_n \in \mathbb{B}^J} p(\mathbf{x}_n|\mathbf{r}_n). \tag{52}$$

Note that in each time instant, the broadcasted message is irrelevant from the the messages in previous time slots. Hence, $\mathbf{x}_n$ does not evolve with time and subscript n can be omitted in the sequel. Since the AP is moving and the signals may be obstructed, the vehicles are not able to acquire the full message, i.e., only part of vector $\mathbf{x}_n$ is observed. Without loss of generality, we consider the binary erasure channel (BEC) model for the lth AP-vehicle link as $\mathbf{h}^{(l)} = [h_1^{(l)}, h_2^{(l)}, \ldots, h_J^{(l)}]^{\mathrm{T}}$, with all entries independent and identically distributed (i.i.d.), obeying Bernoulli distribution

$$h_j^{(l)} = \begin{cases} 0 & \text{with probability } \epsilon \\ 1 & \text{with probability } 1-\epsilon \end{cases}, \tag{53}$$

where $0 < \epsilon < 1$ denotes the erasure probability. With the definition of $\mathbf{h}^{(l)}$, the observation model of the lth vehicle is given by

$$\mathbf{r}^{(l)} = \mathbf{h}^{(l)} \odot \mathbf{x} + \mathbf{z}^{(l)}, \tag{54}$$

where the Gaussian noise $\mathbf{z}^{(l)}$ has a power spectral density (PSD) of N_0. For the centralized network decoding, the fusion centre constructs the factor graph after receiving all observations $\mathbf{r}^{(l)}, \forall l$ from the vehicles and then determines the belief of $\mathbf{x}$ via message passing, formulated as

$$b(\mathbf{x}) \propto p(\mathbf{x}) \prod_{l=1}^{L} \mu_{\mathbf{r}^{(l)} \to \mathbf{x}}(\mathbf{x}). \tag{55}$$

The message $\mu_{\mathbf{r}^{(l)} \to \mathbf{x}}(\mathbf{x})$ is identical to the likelihood function of $\mathbf{r}^{(l)}$ conditioned on $\mathbf{x}$, i.e., $p\left(\mathbf{r}^{(l)}|\mathbf{x}\right)$. Under the assumption that the message $\mathbf{x}$ is generated with equal probability of 0 and 1, to maximize $b(\mathbf{x})$ is equivalent to finding the maximum of the log-likelihood $p(\mathbf{r}|\mathbf{x})$. Since the elements in $\mathbf{x}$ are independent, the estimate of $\mathbf{x}$ can be determined with element-wise operations. For example, the decision of $x_j = 0$ or $x_j = 1$ is made by comparing its log-likelihood ratio (LLR)

$$\gamma_j = \log \frac{p\left(\mathbf{r}_j | x_j = 1\right)}{p\left(\mathbf{r}_j | x_j = 0\right)} \tag{56}$$

with 0, where $\mathbf{r}_j = [r_j^{(1)}, \ldots, r_j^{(L)}]^{\mathrm{T}}$ denotes the vector containing all observations related to x_j. Having (56), the element $x_j = 0$ if $\gamma_j < 0$ and vice versa. After decoding, the RSUs feed back the full message to the vehicles. In the case that an RSU fails to function as normal, all vehicles in its area of coverage cannot receive the full message, leading to tremendous challenges for IVNs.

Next, we show how the message is decoded in a distributed and cooperative way, which is robust to the malfunctions of the RSUs. According to the framework in Section III, we first find the local metric $L(\mathbf{r}^{(l)}, \mathbf{x})$, given by

$$L(\mathbf{r}^{(l)}, \mathbf{x}) = -\frac{1}{2N_0}\mathbf{x}^{\mathrm{T}}\mathrm{diag}[\mathbf{h}^{(l)}]\mathbf{x} + \frac{\mathbf{x}^{\mathrm{T}}\mathrm{diag}[\mathbf{h}^{(l)}]\mathbf{r}^{(l)}}{N_0}. \tag{57}$$

It can be observed that the expression of the local metric $L(\mathbf{r}^{(l)}, \mathbf{x})$ is fully characterized by channel coefficients $\mathbf{h}^{(l)}$. As the global metric $L(\mathbf{r}, \mathbf{x})$ is simply the summation of all local metrics, the vehicles cooperate with their neighbors, then exchange and update channel parameters $\mathbf{h}^{(l)}$ following the consensus operations in Section III-C. After running a few iterations, the vehicles reach consensus on the average of all $\mathbf{h}^{(l)}$. The resultant channel coefficients $\bar{\mathbf{h}}$ are used for calculating the belief $b(\mathbf{x})$ across all vehicles to decode the original message broadcasted from the AP. For the BEC model, exchanging the channel parameters is direct and efficient. However, if the channel model become complex, such as frequency selective channel, sending channel parameters becomes resource inefficient. To this end, we propose an alternative method by exchanging the LLRs of the message among the vehicles in IVN.

Let us reconsider the LLR (56). Since the observations at different vehicles are independent, the distribution $p(\mathbf{r}^j | x^j)$ factorizes as $p(\mathbf{r}_j | x_j) = \prod_{l=1}^{L}(\mathbf{r}_j^{(l)} | x_j)$ and γ_j is rewritten as

$$\begin{aligned} \gamma_j &= \sum_{l=1}^{L} \log \frac{p(\mathbf{r}_j^{(l)} | x_j = 1)}{p(\mathbf{r}_j^{(l)} | x_j = 0)} \\ &= \sum_{l=1}^{L} \gamma_j^{(l)}. \end{aligned} \tag{58}$$

Obviously, the global LLR of decoding a bit in the message $\mathbf{x}$ is the summation of all local LLRs. We stack $\gamma_j, \forall j$, as a vector $\boldsymbol{\gamma}$, which can also be written as $\boldsymbol{\gamma} = \sum_{l=1}^{L} \boldsymbol{\gamma}^{(l)}$, where $\boldsymbol{\gamma}^{(l)} = [\gamma_1^{(l)}, \ldots, \gamma_J^{(l)}]^{\mathrm{T}}$. Consequently, distributedly decoding the full message can be achieved by performing consensus operations of the local LLRs, i.e., with metropolis update weight,

$$\boldsymbol{\gamma}^{(l)}(t) = \xi^{(l,l)}\boldsymbol{\gamma}^{(l)}(t-1) + \sum_{l' \in \mathcal{S}_n^{(l)}} \xi^{(l,l')}\boldsymbol{\gamma}^{(l)}(t-1). \tag{59}$$

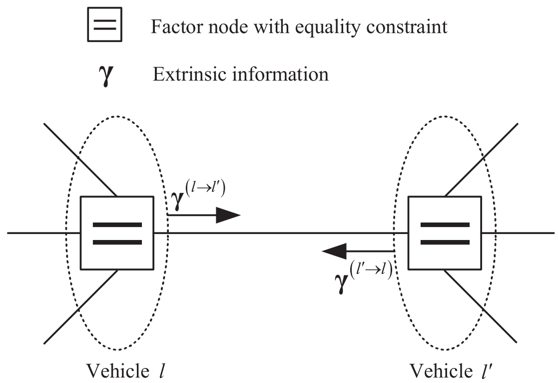


FIGURE 7. **The SPA-based consensus algorithm.**

Let us consider the conventional graph-based decoding algorithm, in which variable nodes send the extrinsic LLRs to the check nodes to update the corresponding information. This procedure is similar to the considered networking decoding problem, in which the check nodes define the equity constraints. Motivated by this, we propose an SPA-based consensus method based on an extended factor graph as shown in Fig. 7. In the graph, all vehicles are generalized as a special type of constraint node, which acquires observations from the channel and performs the LLR updating. In particular, the local LLRs for each vehicle are updated as

$$\boldsymbol{\gamma}^{(l)}(t) = \boldsymbol{\gamma}^{(l\to l)} + \sum_{l' \in \mathcal{S}_n^{(l)}} \boldsymbol{\gamma}^{(l'\to l)}(t-1), \tag{60}$$

where $\boldsymbol{\gamma}^{(l\to l)}$ is defined as the "intrinsic information" representing the information obtained by vehicle l solely based on its observation and $\boldsymbol{\gamma}^{(l'\to l)}(t-1)$ is the "extrinsic information" passed from vehicle l' to vehicle l at the $t-1$th iteration. In particular, we have

$$\boldsymbol{\gamma}^{(l\to l')}(t) = \boldsymbol{\gamma}^{(l)}(t) - \boldsymbol{\gamma}^{(l'\to l)}(t-1). \tag{61}$$

It should be noted that the intrinsic information is purely the information based on the local observation, which remains the same during the iteration. However, the extrinsic information is updated in each iteration according to the messages from neighboring vehicles. The consensus is reached after few iterations, which is similar to the conventional SPA-based decoding algorithms.

Finally, the local LLRs of the vehicles converge to the global LLR and the full message is decoded over the IVN. Compared to the consensus algorithms introduced in Section III-C, the SPA-based consensus method experiences the same benefit as the standard gossip method, which does not need the prior knowledge of the node degree. All vehicles can broadcast their information directly and update their local LLRs based on the received information. Different from the standard gossip method, the convergence speed of the SPA-based approach will not be affected since the local LLRs of all vehicles are updated in each consensus iteration.

Remark 2: For the cooperative network decoding problem, if the vehicles can share the same codebook, we can further achieve some benefits from applying channel coding.

In particular, there are various methods for improving the system performance of distributed estimation. Channel coding has been widely recognized as an efficient method to combat the influence of channel impairments such as fading and noise, thus enabling reliable communication. Therefore, it is natural to expect that channel coding can play an important role in network decoding [118]. In specific, the message broadcasted from the moving AP can be channel-coded, in which case the received message for each vehicle is therefore a part of the codeword that is corrupted by noises. Assuming that the codebook is available for all vehicles, each vehicle can decode the received message individually. After decoding, the extrinsic information of each vehicle in the form of LLR can be exchanged with the neighbouring vehicles in order to reach a common consensus. Compared to the uncoded case, the advantages of cooperative network decoding with channel coding are three-fold: 1) Improved reliability: Since the broadcasted message is channel-coded, the decoding output of each vehicle is then confined within a subspace according to the codebook. A proper designed codebook can eliminate the error patterns with relatively small Euclidean distances and overcome the influence of erasure and noise. 2) Enhanced communication efficiency: Channel coding can help the convergence speed of the graph [119]. In particular, the code can be designed to maximize the mutual information between the broadcasted message and the the extrinsic information from each vehicle in a statistical way according to the channel model. Therefore, the number of required message iterations can be reduced. It has been shown in the literature [120] that a properly designed code over a similar channel model can not only improve the error performance but also provide a significant reduction of required message iterations. 3) Improved resource utilization: Channel coding provides a strong correlation between the symbols in the message. Therefore, it is not necessary to pass all the extrinsic information after decoding to the neighboring vehicles. For instance, it is possible to only pass the information of the data symbols instead of the information of the whole codeword for systematic codes. The neighboring vehicles can simply process the received information by assuming the corresponding information of parity symbols are punctured. Note that, passing partial information may lead to more message iterations. However, this may be potentially valuable in the case of high dynamic vehicle network, where the the message length between neighboring vehicles is strictly limited.

V. NUMERICAL RESULTS

This section presents the simulation results to verify the effectiveness of the proposed distributed estimation framework.

A. SIMULATION SETUP

We consider a vehicular network as shown in Fig. 3, where a dual carriageway of has 4 lanes and each lane has a width of 3.5 m. Without loss of generality, we set the bottom left corner of the road as the origin, denoted by coordinate $[0, 0]^{\mathrm{T}}$. The initial locations of the vehicles are uniformly distributed on the carriageway. The vehicles move along the road with speeds randomly generated from a uniformly distributed random variable with range [10, 15] m/s. The communication range for two vehicles are set to 20 m unless otherwise specified. For the centralized method, the observations from the vehicles are collected by a fusion centre under the assumption of perfect vehicle-RSU links. For the distributed approach, metropolis consensus algorithm is utilized and the maximum iterations for consensus operation is set to $N_{\text{iter}} = 10$. All results are averaged from 1000 independent Monte Carlo trails.

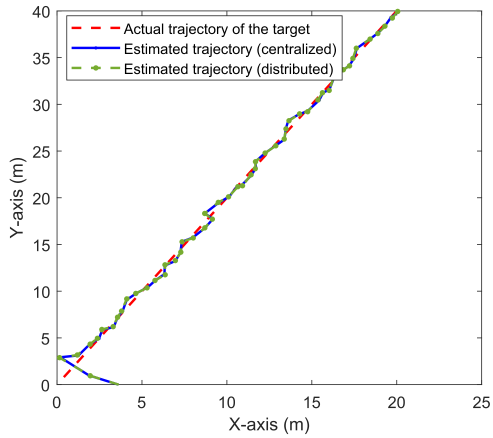


FIGURE 8. **A single trail of target tracking (straight line trajectory).**

B. TARGET TACKING

For the task of external target tracking as in Case I in Section IV, we assume that the observation noise power at reference distance $d_0 = 10$ m is $v_0 = 1\text{m}^2$. The initial guess of the target location is drawn from a Gaussian distribution centered at the actual target location with a standard deviation of 10 m on x and y axes, respectively. In Fig, 8, we illustrate a single trail of the target tracking results with 64 vehicles, where the external target is moving along a straight line. The estimated trajectories of both the centralized and the distributed methods are illustrated. We can see that the proposed factor graph method is capable of accurately tracking the target. It can also be observed the trajectory corresponding to the distributed method almost coincides with that of the centralized method, which validates the accuracy of the proposed distributed estimation framework.

In Fig. 9, we depict the root mean square error (RMSE) of target location based on three consensus algorithms, i.e., the original consensus, the metropolis consensus, and the broadcast gossip algorithms, versus the number of iterations at time instant 50. The RMSE of the centralized method is included as the performance bound, which does not require the consensus iterations. It can be seen from Fig. 9 that the original consensus and the metropolis consensus algorithms converge

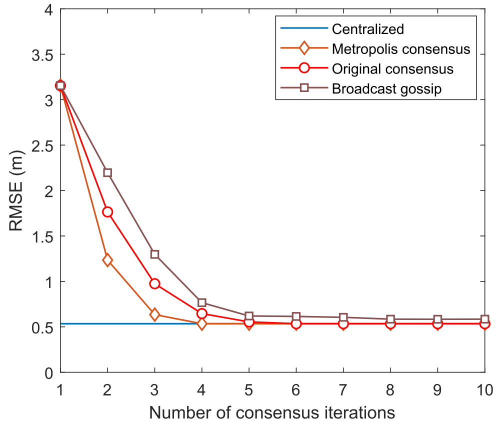


FIGURE 9. The RMSE of the target location versus the number of iterations.

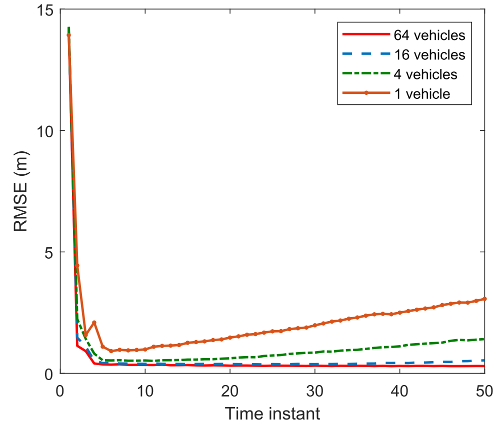


FIGURE 11. The RMSE of the target location versus time index (straight line trajectory).

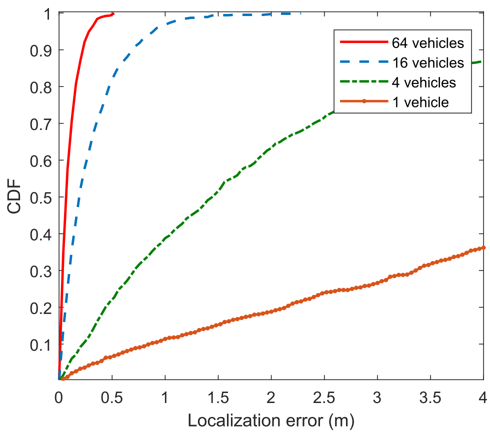


FIGURE 10. The CDF of the target location (straight line trajectory).

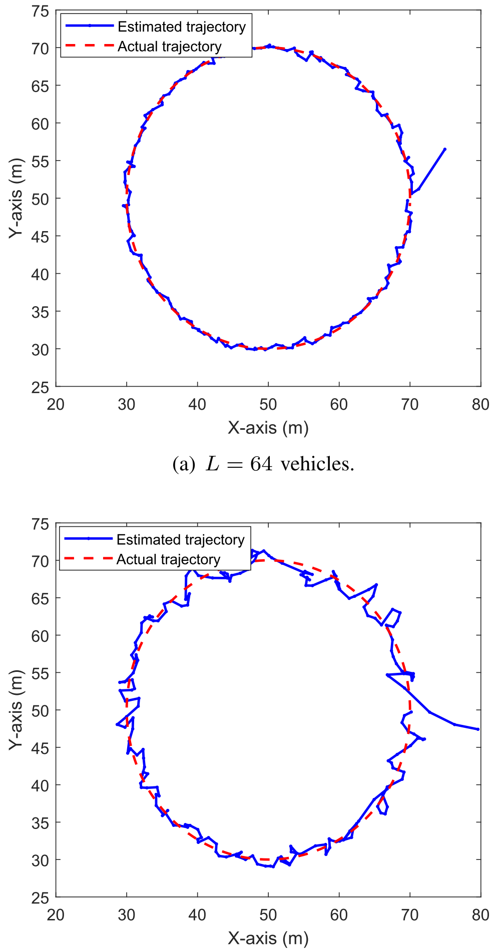
to the performance of the centralized one rapidly after a few iterations, while the broadcast gossip does not converge to the performance bound due to its asymmetrical communication protocols [110]. Compared to the original consensus method and the broadcast gossip one, the metropolis consensus algorithm has the fastest convergence speed due to the use of adaptive weights for different vehicles. We further compare the cumulative distribution functions (CDFs) of tracking error relying on the proposed distributed estimation framework in terms of different number of vehicles, as shown in Fig. 10. Obviously, a higher number of vehicles will lead to more observations of the target and therefore improve the tracking performance. Tracking the target based only on local observations (1 vehicle curve) suffers from significant performance degradation, which shows the benefits of enabling distributed estimation in IVNs for B5G.

Fig. 11 plots the RMSEs of target location versus time instant parameterized by different number of vehicles. We can see that for all cases, the proposed target tracking method can efficiently track the target over time. It is interesting to see that the RMSE curve first decreases and then increases with respect to the time index. This is because when the target is moving away from the vehicles, the observation noise becomes larger and the positioning results are impacted. From Fig. 11, it can be seen that 16 vehicles can provide sufficiently accurate results compared to the case with 64 vehicles case. This motivates us to divide the vehicles into some subgroups and only vehicles in the same subgroup exchange their information. Consequently, the communication signaling overhead of the IVNs can be reduced. In the following, we will consider a more complex circular trajectory to discuss the performance of the proposed distributed algorithm.

In Fig. 12, we demonstrate the results for target trajectory tracking. Compared to the straight line trajectory case, to track the circle trajectory is more challenging since the moving direction of the target varies with time. Two networks with 16 and 64 vehicles are considered. We can see that an IVN with 64 vehicles achieves a high accuracy while the result of using 16 vehicles has localization ambiguity.

Similar to the case of straight line trajectory, we illustrate the CDFs of target location error at time $n = 50$ for $L = 1, 4, 16, 64$ vehicles in Fig. 13. Compared to Fig. 10, we can observe that the performance gap between the plots corresponding to different L becomes larger. The target tracking results relying only on local observations experience a extremely poor performance with more than 90% location errors larger than 4 m. This can be explained by the fact that since the target moving direction varies, the prior information obtained from the state evolution becomes inaccurate. Hence, more observations are demanded to refine the estimation of target location.

Finally we look at the tracking performance in terms of the RMSEs versus time in the circle trajectory case in Fig. 14. As expected, the gaps between each curves become larger than that in the line trajectory case. Moreover, due to the frequent variation of the moving direction of the target, the IVN fails to efficiently obtain the target location in the first few time instants when the number of observations are insufficient. Again, as the target moves towards and away from the vehicles, the RMSEs experience a trend of first decreasing then



(a) $L = 64$ vehicles.

(b) $L = 16$ vehicles.

FIGURE 12. A single trail of target tracking (circular trajectory).

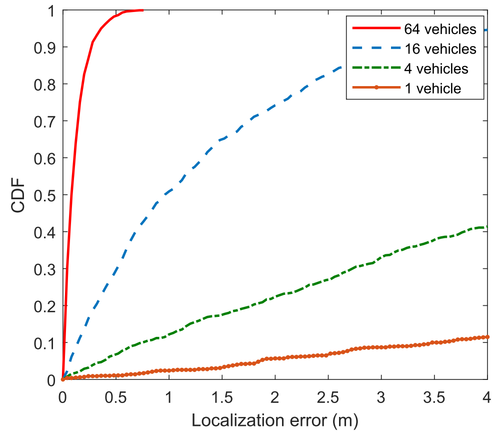


FIGURE 13. The CDF of the target location (circular trajectory).

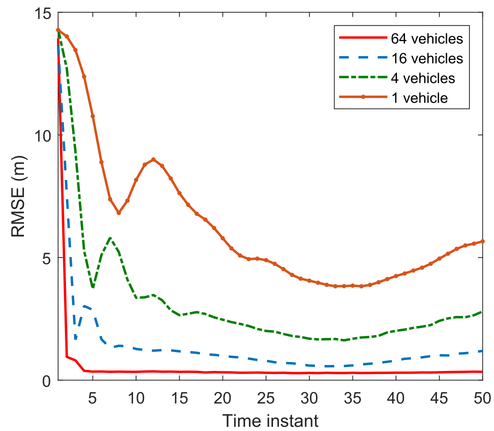


FIGURE 14. RMSE of the target location versus time index (circle trajectory).

fluctuation. To conclude, relying on the proposed distributed estimation framework, the vehicles in the IVN can accurately track the noncooperative moving target. In fact, having more vehicles in network will apparently improve the tracking accuracy, especially when the target adopt a complex moving pattern.

C. NETWORK DECODING

In this subsection, we study the performance of the proposed distributed framework for network decoding. Binary phase shift keying modulation is employed. We consider the information vector $\mathbf{x}$ having a length of 100 and the number of vehicles $L = 64$. The erasure probability is set to $\epsilon = 0.5$, unless otherwise specified. The BER performance are averaged across all vehicles.

We first evaluate the BER-performance of the distributed framework for network decoding in B5G scenarios versus the bit SNR. Again, the BER performance corresponding to the centralized algorithm is used as a benchmark. Distributed algorithm with 1 iteration can be regarded as performing decoding based on only local observations at vehicles. Under this circumstance, the vehicles fail to decode the message from the AP, leading to unacceptably high BER. However, after only two consensus iterations, the BER performance of the distributed framework can attain that of the benchmark algorithm. To further elaborate the convergence behavior of the distributed framework, we illustrate the BER performance versus the number of iterations in Fig. 16, where the number of vehicles is set to be $L = 64$ and the erasure probability is set to be $\varepsilon = 0.5$. Six values of E_b/N_0 are considered. We can observe that for all E_b/N_0 values, the proposed distributed approach can converge after three consensus iterations on average. Besides, further increasing the number of consensus iterations can improve the performance but the gain is only marginal. Therefore in practical B5G IVNs, we can choose a relatively small number of iterations for decoding while preserving an excellent performance, especially for low SNRs.

In Fig. 17, we compare the BER performance in terms of different communication ranges. The maximum number of consensus iterations is set to 3 to reduce the decoding complexity. It can be seen that the increase of the communication range leads to better decoding performance. The reasons for

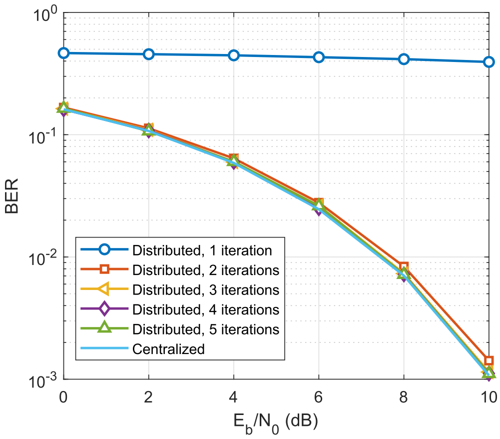


FIGURE 15. BER of the proposed algorithm versus E_b/N_0 with different number of iterations.

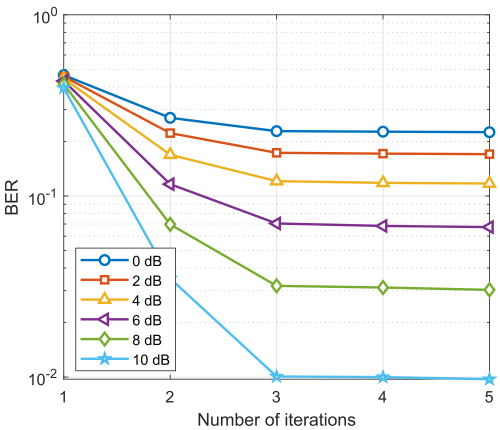


FIGURE 16. BER of the proposed algorithm versus the number of iterations parameterized by different E_b/N_0.

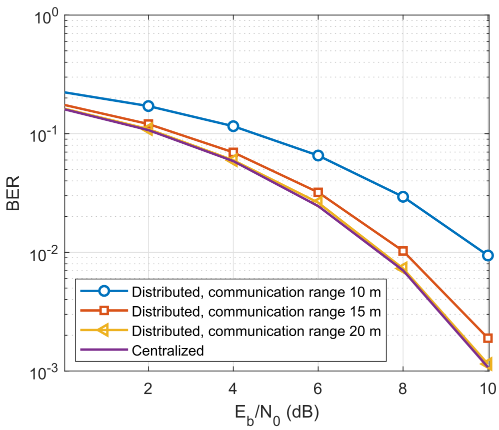


FIGURE 17. BER of the proposed algorithm versus E_b/N_0 with different communication range.

the performance loss in the scenarios with 10 m and 15 m are two-fold. The first one is that when the communication range is small, the resultant graph $\mathcal{G}$ may not be connected. A vehicle has no neighbors will fail to decode the message and degrade the average BER performance. Another reason

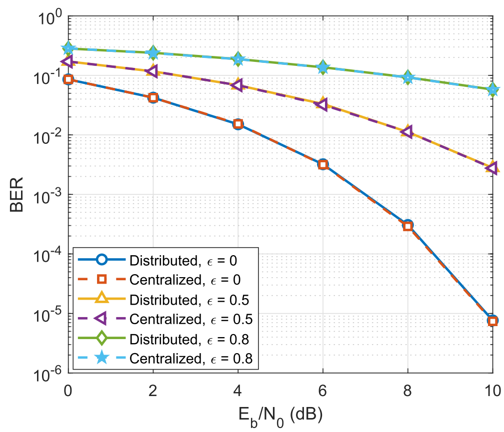


FIGURE 18. The system BER versus E_b/N_0 for various erasure probabilities.

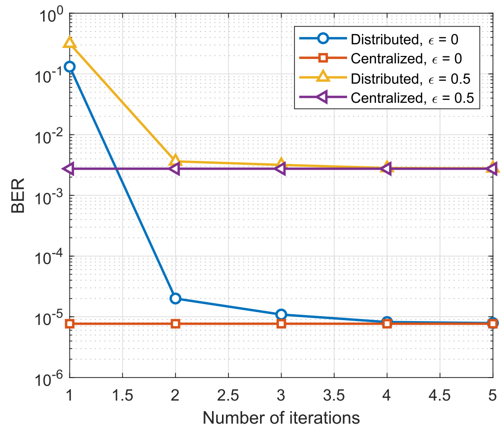


FIGURE 19. Convergence of the proposed distributed network decoding approach.

is the proposed distributed processing framework depends on a multi-hop routing scheme. For an isolating vehicle which has only one neighbor, the connection with other neighbors requires several hops. Thus, a higher number of iterations is needed for the network to reach consensus.

In Fig. 18, the impact of the erasure probability is considered in an IVN with $L = 16$ vehicles. Three cases with probabilities of $\xi = 0, 0.5$, and 0.8 are illustrated for both centralized and distributed implementations. Specifically, $\epsilon = 0$ corresponds to AWGN channel. In all three cases, the BERs of the distributed framework converge to the corresponding centralized performance, verifying the effectiveness of the distributed framework in handling network decoding problems.

Let us now characterize the convergence of the proposed distributed algorithm in Fig. 19, where the SNR is set as $E_b/N_0 = 10$ dB and the number of vehicles is $L = 16$. We observe that the distributed algorithm can converge to the centralized one after 4 consensus iterations for both $\epsilon = 0$ and $\epsilon = 0.5$. The similar convergence trends show that the convergence behavior of the cooperative network decoding is

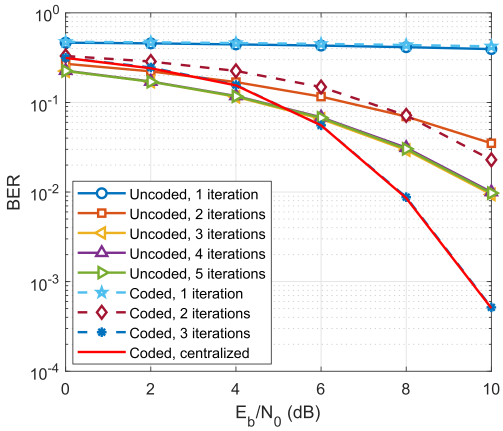


FIGURE 20. Comparison of uncoded and coded systems.

dominated by the network topology instead of the channel parameters. Moreover, for the case with a larger ϵ, the BER after the second iteration is close enough to that of the benchmark, which validates our aforementioned discussion on the reduced number of iterations.

We finally show the benefits of employing channel-decoding by comparing the BER performance of uncoded and coded systems in Fig. 20. We employ a rate-$1/2$ feed-forward (7, 5) convolutional code. It can be observed in this figure that in the high SNR regimes, the BER performance of coded systems is better than that of the uncoded systems. In particular, the BER performance of the coded system with 3 iterations has a 2 dB gain over the uncoded systems with 5 iterations. This indicates that the channel coding not only improves the error performance but also requires less number of consensus iterations compared to the uncoded systems. On the other hand, the BER performance of both coded and uncoded systems converges to the centralized performance with only 3 consensus iterations. This clearly substantiates the proposed distributed framework.

VI. FUTURE WORKS AND CONCLUSIONS

We have introduced a distributed estimation framework and emphasized its benefits for B5G IVNs. This section will first provide some challenges and future works for the development of distributed estimation for IVNs. Then we will summarize this paper and draw some conclusions.

A. CHALLENGES AND FUTURE WORKS

1) Security Issues
Although distributed estimation and detection has shown its potentials in IVNs for different applications, it also raises the concerns of security and privacy. For instance, vehicles share the information with their neighboring vehicles in each consensus iteration. This protocol may inadvertently lead to the leakage of some confidential information to unauthorized users [121]. In a worse case, the existence of eavesdroppers or malicious users will result in severe security issues. Therefore, the physical security issue is of high importance for distributed estimation in IVNs. A possible solution is to exploit the techniques from the physical layer security broadcast artificial noise to contaminate the received signaling of malicious users [122]–[124]. However, how to ensure the secrecy of information transmission in distributed estimation for IVNs is still challenging and needs to be investigated.
2) Imperfect Vehicle States
Throughout this paper, we assume that the states of vehicles are perfectly known. However, this information is not always available, especially in some harsh environments where the sensors on vehicles are not working. It is a crucial requirement to accurately obtain the vehicle states in order to fulfill the function of sensing the environments. Thus, simultaneous estimating both the unknown variables and the vehicle states could be one of the future topics. Moreover, the uncertainty of the vehicle states should be taken into account when performing distributed estimation and detection. Also, the way to merge the information related to vehicles and to unknown variables is still not clear. Our distributed estimation framework is potential to address this challenge by adding corresponding variable nodes to factor graph and implementing the message passing algorithm. Some initial attempts in the literature can be found in [125], [126].
3) Communication Aspects
Wireless communication is the key enabler for realizing the potentials of IVN in the future B5G wireless networks. In particular, millimeter wave (mmWave) communication [127]–[129] has been widely recognized as an enabling technology to meet the needs of data-intensive applications in future in-vehicle infotainment systems. Besides, the abundant spectrum in the mmWave frequency band can be exploited for accurate localization and tracking of vehicle. New distributed mmWave systems [130] should be developed for catering the inherent distributed property in signal processing and communications of IVN. Besides, robust and fast beam alignment should be addressed in the highly mobile mmWave IVN. In addition, to accommodate the massive number of vehicles in IVN with limited resources, novel multiple access schemes, such as random access [131]–[133], need to be proposed for facilitating spectrally and energy-efficient communications [134], [135]. How to evaluate the performance gain of NOMA in IVNs and how to efficiently allocate the system resources are main challenges remained to be tackled.
4) Learning-Assisted Distributed Signal Processing
Recently, deep learning (DL) technology utilizing a deep neural network (DNN) can intelligently explore the features from different environments in a data-driven manner [136]. It has shown its great potentials in the future wireless communications, to solve the

problems of signal detection [137], classification [138], and sensing [139]–[141] while achieving satisfactory performance. For the distributed signal processing in IVNs, all vehicles can cooperative to use the same DNN structure to extract common features. Then the common DNN structure can be reused by different vehicles by adjusting the DNN to satisfy their requirements, which may achieve good performance with a relatively low overhead. How to share the environment variations and adjust the DNN across the vehilces are still under investigation. It is believed that the learning-assisted distributed signal processing is of great importance in the future IVNs.

5) Joint Sensing and Communication Designs
As a pair of essential functionalities in the IVNs, communication and sensing are envisioned to be intertwined. Having a single-device providing both sensing and communication functionalities is expected to significantly reduce the hardware complexity associated with the sensors mounted on vehicles or road infrastructures, while improving the overall performance. To this end, research efforts towards dual-functional radar-communication (DFRC) systems are well underway [142]. While existing schemes have addressed the DFRC design issues for general cellular transmission [143]–[146], the specific joint sensing and communication approach tailored for V2X scenarios remains widely unexplored. Some initial ideas on this topic can be found in recent work, e.g., [147].

B. CONCLUSIONS

The awareness of environments at vehicles is one of the key features in B5G IVNs. Unlike current vehicular networks relying on feedback-based schemes, the future IVN should be resilient to possible link failures and malfunctions of the RSUs. In this paper, we have provided an overview of the communications and signal processing problems in vehicular networks. From the viewpoint of detection and estimation, the parameters of environments are obtained using the collected observations via appropriate estimation methods. Then, we established the general framework for estimating the variables of interest and proposed a factor graph method for inferring the variables.

By enabling cooperations amongst the vehicles, we proposed the distributed implementations of the aforementioned factor graph approach. Relying only on local computations and communications with neighbors, all connected vehicle are capable of determining the variables without the help of the RSUs. Compared to the centralized method, the distributed method has the benefits of high scalability and robustness. We further introduced three approximations for reducing the communication overhead of consensus operations. Then we studied two cases of distributed target tracking and cooperative network decoding to show that the proposed framework is flexible and can be modified to fit different problems in IVNs. Simulation results verify the effectiveness of the proposed algorithms, showing the potential of the distributed framework in solving several practical applications in IVNs for the future B5G wireless communications.

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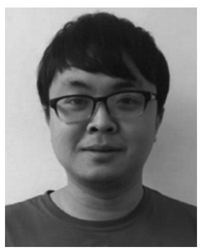

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