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Social Big Data based Content Dissemination in Internet of Vehicles

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***Abstract*—By analogy with internet of things (IoT), internet of vehicles (IoV) which enables ubiquitous information exchange and content sharing among vehicles with little or no human intervention is a key enabler for the intelligent transportation industry. In this paper, we study how to combine both the physical and social layer information for realizing rapid content dissemination in device-to-device vehicle-to-vehicle (D2D-V2V) based IoV networks. In the physical layer, headway distance of vehicles is modeled as a Wiener process, and the connection probability of D2D-V2V links is estimated by employing the Kolmogorov equation. In the social layer, the social relationship tightness that represents content selection similarities is obtained by Bayesian nonparametric learning based on real-world social big data, which are collected from the largest Chinese microblogging service Sina Weibo and the largest Chinese video-sharing site Youku. Then, a price-rising based iterative matching algorithm is proposed to solve the formulated joint peer discovery, power control, and channel selection problem under various quality of service (QoS) requirements. Finally, numerical results demonstrate the effectiveness and superiority of the proposed algorithm from the perspectives of weighted sum rate and matching satisfaction gains.**

***Index Terms*—internet of things, internet of vehicles, D2D-V2V, content dissemination, social big data, matching theory, Youku, Sina Weibo.**

I. Introduction

A. Background and Motivation

WITH the evolutionary growth of internet of things (IoT), it is estimated that almost 50 billion devices will be interconnected by 2020, and the generated data traffic will grow by another 1000 times [1], [2]. As a typical example of IoT, internet of vehicles (IoV) which supports ubiquitous information exchange and content sharing among vehicles with little or no human intervention is a key enabler for the intelligent transportation industry. It provides unprecedented opportunities and capability for vehicle vendors and service providers to develop new applications with multimedia-rich contents such as route planning, collision warning, online games, traffic monitoring, and so on. However, IoV also raises new challenges to vehicle-to-vehicle (V2V) communication technologies. The gap between the rapidly growing demands of data rate and the limited network bandwidth has become ever prominent.

There are two major V2V solutions, i.e., the ad-hoc-based IEEE 802.11p standard and infrastructure-based cellular technologies such as long term evolution (LTE) [3]. On one hand, the IEEE 802.11p adopts the legacy carrier sense multiple access with collision avoidance (CSMA/CA) mechanism for access control, which is originally designed for wireless local area network type communications and is not optimized for fast moving vehicles. It is difficult to realize reliable service delivery and coordinated resource allocation in ad-hoc fashioned V2V communications due to the lack of centralized intelligence. On the other hand, LTE-based V2V solution poses a heavy burden on the capacity and delay constrained backhaul links, and may even worsen the cell overload problem. Hence, new V2V technologies which can leverage widespread cellular infrastructures and underutilized frequency spectrums are urgently required.

Device-to-device (D2D) communication, which allows direct data transmission over proximate peer-to-peer links with the assistance of centralized infrastructures, has emerged as a promising candidate for future IoV networks. D2D-V2V (D2D-V2V) communication can significantly reduce transmission latency and improve spectrum efficiency due to the proximity gain, hop gain, and reusing gain [4]. In particularly, effective vehicle-to-infrastructure (V2I) data offloading can be achieved through D2D links. For an instance, multiple vehicular users heading toward the same direction usually request very similar contents such as road and traffic information, which have to be transmitted by the base station through multiple repeated transmissions. In comparison, D2D-V2V allows direct content sharing or pushing among vehicles with similar interests without going through the base station.

However, the successful implementation of D2D-V2V based content dissemination remains nontrivial. First of all, the diverse content preferences of vehicular users have to be taken into consideration during the D2D-V2V peer discovery process in order to realize effective content dissemination and

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achieve high content matching satisfactions. In this paper, we use *social relationship tightness* to reflect the content selection similarities of different vehicular users. Secondly, the fast mobility features of vehicles make the D2D-V2V links highly dynamic and unreliable. A critical challenge is how to explore long-lasting and reliable D2D-V2V connections for effective content dissemination. Last but not least, co-channel interference caused by cellular spectrum reusing must be well managed to optimize system performance while meeting quality of service (QoS) requirements. Combining the above three aspects, it is intuitive to combine both social and physical layer information for optimizing D2D-V2V based content dissemination.

B. State of the Art

Two major bottlenecks of implementing D2D communications are limited frequency spectrum and constrained battery capacity. Hence, conventional studies mainly aim at optimizing either spectrum efficiency or energy efficiency. Spectrum-efficient resource allocation problems have been investigated in various application scenarios such as relay-aided D2D networks [5], mobile content delivery [6], and mobile social networks [7], etc. For energy-efficient resource allocation design, matching theory and game theory have been widely employed to optimize power control [8], [9]. Energy harvesting technologies such as simultaneous wireless information and power transfer (SWIPT) were utilized to improve energy efficiency by exploring external energy sources [10]. The tradeoff between energy efficiency and spectrum efficiency of D2D communications was analyzed in [11], [12].

For D2D-V2V based IoV networks, performance analysis in terms of outage probability and spectrum efficiency was performed in [13], [14]. Given the latency and reliability constraints, cluster-based and separate resource block sharing and power allocation algorithms for D2D-V2V communications were proposed in [15] and [4], respectively. In [3], the authors proposed a greedy-based resource allocation algorithm to minimize the end-to-end delay by exploring both D2D and IEEE 802.11p. A D2D-V2V framework which consists of vehicle grouping, channel selection, and power allocation was proposed in [16]. In [17], two distributed resource allocation schemes were proposed for D2D-based safety-critical vehicular network with unlicensed band access. A matrix game based resource sharing approach was proposed in [18] to optimize geodistributed cloudlet resource management and allocation in D2D-based vehicular networks. In [19], the authors investigated the user-priority-based power control problem by optimizing individual channel rates with the consideration of cross-tier interference and electromagnetic interference in D2D-assisted IoV network. These works mainly focus on the physical layer information, and the utilization of social layer information has not been well investigated.

There exist some works on V2I data offloading by integrating IoV networks with social layer information [20]–[24]. In vehicular social applications such as "Road Speak" [20], "Road Sense" [21], and "Social Drive" [22], etc., social connections among users are employed to recommend chat groups with similar interests, and to share real-time road traffic, road conditions, and driving experience. In [23], the authors presented an review of social IoV networks, and proposed a communication message structure based on SAE J2735. A social-aware friend recommendation system named Verse was proposed in [24], which is based on keywords of interests and requires no Internet connection. A cooperative delay-tolerant content dissemination strategy was proposed in [25] for vehicular networks with the aim of minimizing cellular traffic load. Both Wi-Fi based V2I and ac-hoc based V2V communications were employed to offload a significant portion of cellular data traffic. In [26], the authors investigated energy-efficient multimedia data dissemination problem in a vehicular cloud environment by formulating a stochastic reward nets-based coalition game, in which a demand- and supply-based payoff mechanism was proposed for each vehicle in the game.

However, most of the above works were developed based on IEEE 802.11 serial standards, and the specific characteristics of D2D-V2V communications have been largely neglected. D2D-based content delivery problem with parked vehicles was studied in [27]. The authors presented detailed introduction about interest sending, content distribution, and content replacement. By analogy with the concept of biologic swarms, a swarm-based social-aware IoV framework was proposed in [28]. The authors presented typical application scenarios of social vehicle swarms, and identified several key technologies including D2D, mobile edge computing, deep reinforcement learning, and privacy preserving data mining. In [29], the authors proposed a D2D-based vehicular social network architecture named VeShare by exploring data-control plane separation. The control plane determines social network association and resource allocation, while the data plane is only responsible for data collection and transmission. In [30], a heterogeneous offloading framework was designed to deliver delay-tolerant smart grid data in a store-carry-forward fashion by exploring vehicle-assisted D2D networks. A dynamic mode selection and resource allocation algorithm was developed to optimize the total average delivery ratio while guaranteeing the smart grid user fairness. Different from these works, real-world social big data is not incorporated in [27]–[30], and the joint optimization of peer discovery, power control, and channel selection involved in D2D-V2V based content dissemination has not been well investigated.

C. Contribution

The major contributions of this paper are summarized as follows.

- We propose a social big data-based content dissemination approach for offloading V2I data traffic through D2D-V2V links. We combine both the physical and social layer information in IoV networks for the optimization of content dissemination. In the physical layer, the headway distance of vehicles traveling in the same direction is modeled as a Wiener process, and the connection probability of D2D-V2V links is estimated by exploring the Kolmogorov equation. In the social layer, the social

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relationship tightness in terms of content selection similarity is obtained by Bayesian nonparametric learning (BNL) based on real-world social big data, which are collected from the largest Chinese microblogging service *Sina Weibo* and the largest Chinese video-sharing site *Youku*.

- We formulate a joint peer discovery, power control, and channel selection problem for the optimization of content dissemination. The objective is to maximize the D2D-V2V sum rate which is weighted by social relationship tightness and connection probability. Since the formulated joint optimization problem involves a three-dimensional matching among vehicular content providers, content consumers, and cellular spectrum resources, it is NP-hard due to the combinatorial nature. To provide a tractable solution, spectrum resources and content consumers are combined to reduce matching dimensionality. We model the preference of a content provider over a combined resource-consumer unit as the maximum achievable weighted rate, which can be obtained by solving a power control problem under QoS constraints of both cellular and D2D-V2V links. Then, a price rising strategy is proposed to resolve the contention when multiple content providers prefer to be matched with the same spectrum resource or content consumer.
- We analyze the proposed algorithm from the perspectives of stability, convergence, optimality, and computational complexity. The proposed algorithm is compared with exhaustive and random matching algorithms from the perspectives of weighted sum rate and matching satisfaction under different scenarios. Numerical results demonstrate that significant performance gains can be achieved by incorporating social big data into vehicular content dissemination.

The remaining parts of this paper are organized as follows. Section II presents the system model of both physical and social layers. The formulation of content dissemination problem is provided in section III. Section IV describes the preference modeling and the proposed price-rising based three-dimensional iterative matching algorithm. Simulation results and relative discussions are presented in section V. Section VI concludes the paper and identifies future research directions.

II. System Model

Fig. 1 shows the D2D-V2V based IoV network, which consists of one base station, multiple cellular user equipments (CUEs) and potential D2D-V2V pairs. CUEs which include both vehicles and smart phones can communicate with the base station by using orthogonal spectrum resource blocks (RBs). In this paper, we assume that the mode selection process is already finished, and there exist some D2D-V2V based vehicular transmitters (content providers) and receivers (content consumers), which are denoted as V-TXs and V-RXs, respectively. We focus on how to match V-TXs and V-RXs, allocate transmission power, and select RB to maximize the transmission rate, which involves the joint optimization of peer discovery, power control, and channel selection.

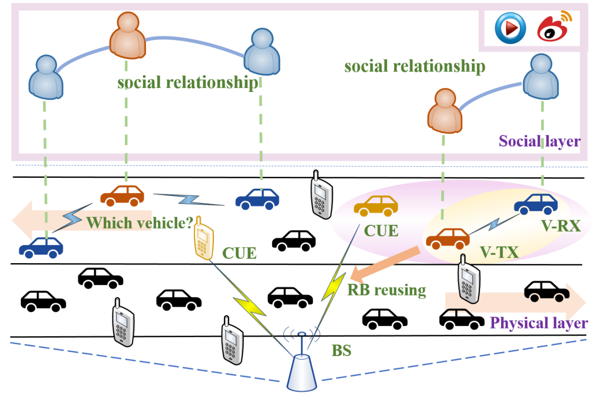

Fig. 1: The physical layer and social layer models of D2D-V2V based IoV networks.

A V-TX and a V-RX are allowed to form a D2D-V2V pair for content dissemination if and only if certain physical and social layer requirements are satisfied. In the physical layer, the establishment of a D2D-V2V link depends on the connection probability due to the dynamic and unreliable connections caused by high mobility of vehicles [4], [14]. In the social layer, the preferences of contents are reflected by vehicular users' behaviors in social networks, from which real-world social big data can be obtained to estimate the content selection similarities between V-TXs and V-RXs in terms of social relationship tightness. In general, it is intuitive to allow vehicles with good channel conditions, long-lasting connections, and similar content preferences to form D2D-V2V pairs. Hence, both the physical and social layer information should be utilized to optimize content dissemination. In this section, the physical layer models including channel model and connection probability estimation are described firstly in subsection II-A, and then the social relationship tightness between vehicles is quantified in subsection II-B.

A. Physical Layer Model

In this subsection, we introduce the channel model and connection probability estimation.

1) Channel Model: We consider the uplink spectrum sharing scenario where each D2D-V2V pair can reuse at most one uplink orthogonal RB allocated to a CUE for data transmission. We assume that there exist M V-TXs and M V-RXs in the IoV network, which are denoted by the sets $\mathcal{V_T} = \{V_1^T, V_2^T, \cdots, V_i^T, \cdots, V_M^T\}$ and $\mathcal{V_R} = \{V_1^R, V_2^R, \cdots, V_j^R, \cdots, V_M^R\}$, respectively. The K RBs and the corresponding CUEs are denoted by the sets $\mathcal{C} = \{C_1, C_2, \cdots, C_k, \cdots, C_K\}$, and $\mathcal{C_V} = \{C_1^V, C_2^V, \cdots, C_k^V, \cdots, C_K^V\}$, respectively. Owing to spectrum reusing, V-TXs cause co-channel interference to the base station, and V-RXs receive co-channel interference from CUEs.

It is extremely difficult to estimate real-time channel state information (CSI) due to the fast channel variations caused by vehicle mobility. Previous works have demonstrated that the mere consideration of large-scale fading effects such as

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pathloss results in little performance degradation [4], [13], [14]. Hence, we only consider the free space propagation pathloss and ignore the small-scale fading effects.

Assuming that V-TX V_i^T and V-RX V_j^R form a D2D-V2V pair V_{ij} by reusing the RB C_k allocated to CUE C_k^V, the spectrum efficiency (defined as bits/Hz/s) performances of D2D-V2V pair V_{ij} and CUE C_k^V are given by

$$r_{V_{ij},k} = \log_2\left(1 + \frac{P_{V_{ij},k} d_{ij}^{-\alpha_v}}{P_k d_{kj}^{-\alpha_{cv}} + N_0}\right), \tag{1}$$

$$r_{k,i} = \log_2\left(1 + \frac{P_k d_k^{-\alpha_c}}{P_{V_{ij},k} d_{iB}^{-\alpha_{vc}} + N_0}\right), \tag{2}$$

where $P_{V_{ij},k}$ and P_k are the transmission power of V_i^T and C_k^V, respectively. d_{ij} and d_k denote the transmission distance of the D2D-V2V link and the cellular link, respectively. d_{kj} denotes the transmission distance between CUE C_k^V and V-RX V_j^R, while d_{iB} is the transmission distance between V-TX V_i^T and the base station. We use different pathloss components for cellular and D2D-V2V links. That is, the pathloss exponents corresponding to the cellular link, the D2D-V2V link, the interfering link from CUEs to V-RXs, and the interfering link from V-TXs to the base station are represented as α_c, α_v, α_{cv}, α_{vc}, respectively. N_0 is the one-sided power spectral density of additive white Gaussian noise (AWGN).

2) Connection Probability Estimation: The mobility pattern of vehicles and the connection probability estimation have been intensively studied in previous works [24], [31]. We adopt the method proposed in [24] to predict the connection probability between two vehicles. The approach is briefly introduced here, and more details can be found in [24] and the references therein.

Taking D2D-V2V pair V_{ij} as an example, the mean and variance of velocities corresponding to V_i^T and V_j^R are denoted as v_i, σ_i^2 and v_j, σ_j^2, respectively. The D2D-V2V communication range is assumed to be L. The headway distance from V_i^T to V_j^R after time t is denoted as $H(t)$, e.g., $H(t) > 0$ represents that V-TX V_i^T is ahead of V-RX V_j^R, and $H(t) \leq 0$ otherwise. The initial value of $H(t)$ is set as h_0.

The connection time is evaluated by the mean first passage time T, which is a random variable depending on initial headway distance and velocity differences. T is given by

$$T = \{\min t \mid H(t) = h_0, -L < H(x) < L, 0 \leq x \leq t\}. \tag{3}$$

In order to evaluate T, the headway distance $H(t)$ is modeled as a Wiener process. The drift and variance are denoted as $\mu = v_i - v_j$ and $\sigma^2 = \sigma_i^2 + \sigma_j^2$, respectively. The increment of $H(t)$ within the infinitesimal interval Δt follows a normal distribution, which is given by

$$\Delta H(t) = H(t + \Delta t) - H(t) = \mu \Delta t + \sigma W, \tag{4}$$

where W obeys the normal distribution with mean zero and variance Δt, i.e., $W \sim \mathcal{N}(0, \Delta t)$. Since time evolution of the probability density function (PDF) of a particle's velocity in Winer Process can be described by the Kolmogorov equation, we have

$$\frac{\partial p(\tau \mid h_0, t)}{\partial t} = -\mu \frac{\partial p(\tau \mid h_0, t)}{\partial \tau} + \frac{1}{2}\sigma^2 \frac{\partial^2}{\partial \tau^2} p(\tau \mid h_0, t), \tag{5}$$

where $-L \leq \tau \leq L$, and $p(\tau \mid h_0, t)$ is the PDF of $H(t)$ conditioned on $H(0) = h_0$. Define $\delta(.)$ as the Dirac delta function, the initial and boundary conditions are given by

$$p(\tau \mid h_0, 0) = \delta(h_0), \tag{6}$$

$$p(-L \mid h_0, t) = p(L \mid h_0, t) = 0, t > 0. \tag{7}$$

By combing (5) $\sim$ (7), $p(\tau \mid h_0, t)$ is obtained as

$$p(\tau|h_0, t) = \frac{1}{\sqrt{2\pi\sigma^2 t}} \sum_{y=-\infty}^{\infty} \Bigg[\exp\left\{ \frac{4y\mu L}{\sigma^2} - \frac{[(\tau - h_0) - 4yL - \mu t]^2}{2\sigma^2 t} \right\} - \exp\left\{ \frac{2\mu L(1-2y)}{\sigma^2} - \frac{[(\tau - h_0) - 2L(1-2y) - \mu t]^2}{2\sigma^2 t} \right\} \Bigg]. \tag{8}$$

The cumulative distribution function (CDF) of the connection time T can be derived based on (3),

$$F_{ij}(t) = \Pr\{T \leq t\} = 1 - \int_{-L}^{L} p(\tau \mid h_0, t) d\tau, \tag{9}$$

which is defined as the probability that V_i^T and V_j^R are connected within duration t.

The evaluation of vehicle connection time depends on initial headway distance and velocity difference, which in essence are closely related to key mobility features including vehicle density, velocity and traffic dynamic. For example, considering the traffic jam scenario with ultra-high vehicle density, the velocity difference between two vehicles that are stuck in the middle of a long queue tends to be decrease. This effect can be well captured in simulations by adjusting mean and variance values of vehicle velocities, which results in longer connection time and larger probability of establishing more long-lasting and reliable D2D-V2V connections. Hence, the impacts of vehicle density, velocity, and traffic dynamic on numerical results are reflected through connection probability, and the solution derived in this work can be applied for numerous IoV application scenarios.

B. Social Layer Model

In the social layer, we employ BNL to obtain the social relationship tightness in terms of content selection similarity by exploring social big data obtained from Sina Weibo and Youku, which are real-world data corresponding to IoV users. Actually, since the content preferences of IoV users generally change slowly compared to channel variations, it is not necessary to collect and process social big data in real time, which is both time consuming and costly. Hence, the social big data can be collected and analyzed in an off-line manner, e.g., even when an IoV user is not in a vehicle. Although this work only involves social big data from Sina Weibo and Youku, it also sheds lights into future works which incorporate multi-dimensional big data from a large number of mobile Internet applications for finer granularity analysis.

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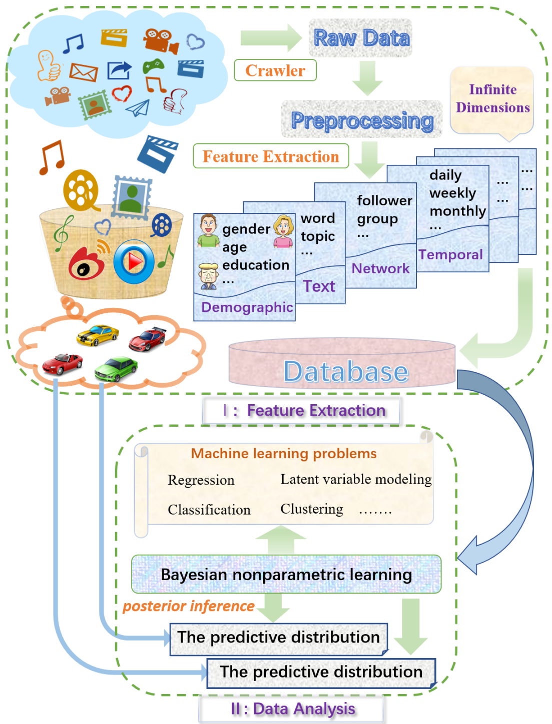

Fig. 2: The BNL-based social relationship estimation by exploring real-world social big data from Sina Weibo and Youku.

1) Data Collection and Preprocessing: We have crawled the Sina Weibo site and retrieved billions of tweets from one thousand active users within a time span of two years. It is interesting to note that Sina Weibo users frequently share their preferred video clips on their microblogs via a short URL, which links to the video entry on Youku. The features of each video in Youku can be extracted from the profile page through Youku's API, which contains video title, category, view numbers (popularity), interest tags, and related videos.

Upon collecting the huge volume of data, data preprocessing is performed to improve the data quality. We apply data cleaning to remove noise and resolve inconsistencies. For an instance, Weibo users with too little information on their public profiles should be filtered out to avoid confusion [32]. Video tags from Youku have to be augmented with semantic knowledge to solve the challenges raised by tag ambiguity and heterogeneity [33]. Afterwards, important features related to content preference in terms of demographic attribute (gender, marital status, education level, career, hobby, etc.), text attribute (topic distribution, word contextual semantics), network attribute (social connections), and temporal attribute (daily/weekly/monthly activity distribution) are extracted to form the dataset.

2) Social Relationship Estimation: Due to the huge dimensionality and high complexity of user content preferences, parametric learning approaches with a fixed parameter space are not suitable. Hence, we adopt a nonparametric and unsupervised learning scheme, i.e., BNL, in which the complexity of the model is allowed to grow and the accuracy of the estimation will be improved as the size of observed data becomes larger [34]. BNL places a prior distribution on an infinite dimensional parameter space to avoid overfitting or underfitting of the data, and estimates the posterior distribution directly by invoking only a finite subset of available parameters.

Denoting the set of users as $\mathcal{U}=\{1,\cdots,U\}$, for any user $u\in\mathcal{U}$, we assume that S observation sets which contain the probability of selecting similar contents can be obtained from the dataset. The set of observation sets is defined as $\mathcal{S}=\{1,\cdots,S\}$. For any observation set $s\in\mathcal{S}$, the probability of selecting similar contents for user u is denoted as p_{su}, which is a random variable with a PDF $P_{su}(p_{su})$ over the space $\Theta=[0,1]$. Dirichlet process, which is a flexible and nonparametric prior over an infinite dimensional parameter space in BNL model, is employed to model the prior information of the probability distribution [35]. For any observation set $s\in\mathcal{S}$, we perform N_{su} observations, which are denoted as $\mathcal{N}_{su}=\{p_{su}^1,p_{su}^2,\cdots,p_{su}^{N_{su}}\}$. Based on $\mathcal{N}_{su}$, the PDF of the next observation $p_{su}^{N_{su}+1}$ is calculated as

$$P_{su}(p_{su}^{N_{su}+1}\in\varepsilon|p_{su}^1,p_{su}^2,\cdots,p_{su}^{N_{su}})=\frac{1}{\varsigma+N_{su}}\Big(\varsigma A(\varepsilon)+\sum_{n=1}^{N_{su}}\varpi_{p_{su}^n}(\varepsilon)\Big). \tag{10}$$

ε is a measurable partition of Θ. A and ς are the base distribution and concentration parameter of the Dirichlet process, respectively. Since A and ς are unknown, $P_{su}(p_{su}^{N_{su}+1}\in\varepsilon\mid p_{su}^1,p_{su}^2,\cdots,p_{su}^{N_{su}})$ can be calculated as

$$P_{su}(p_{su}^{N_{su}+1}\in\varepsilon|p_{su}^1,p_{su}^2,\cdots,p_{su}^{N_{su}})=\frac{\sum_{n=1}^{N_{su}}\varpi_{p_{su}^n}(\varepsilon)}{N_{su}}, \tag{11}$$

where $\varpi_{p_{su}^n}$ is the point mass at p_{su}^n. $\varpi_{p_{su}^n}(\varepsilon)=1$ when $p_{su}^n\in\varepsilon$, and $\varpi_{p_{su}^n}(\varepsilon)=0$, otherwise.

The estimation accuracy can be further improved by incorporating new observations from the subset $\mathcal{Q}\in\mathcal{S}$. Denoting $\mathcal{Q}_{su}=\mathcal{Q}\backslash\{\mathcal{Q}\cap s\}$ as the observation sets in $\mathcal{Q}$ excluding $\mathcal{Q}\cap s$, the PDF of the next observation $p_{su}^{N_{su}+1}$ can be calculated by combining both s and $\mathcal{Q}_{su}$ as

$$P_{su}^{\mathcal{Q}}=\varrho_s\tilde{P}_{su}(\varepsilon)+\sum_{z\in\mathcal{Q}_{su}}\varrho_z\tilde{P}_{zu}(\varepsilon). \tag{12}$$

ϱ_s and ϱ_z are the weights corresponding to the contribution of s and z ($z\in\mathcal{Q}_{su}$), respectively. Due to the unbiased nature of each observation set, we have $P_u=P_{su}^{\mathcal{Q}}$, where P_u represents the PDF corresponding to the probability distribution of selecting similar contents for user u.

3) Social Relationship Tightness: For V-TX V_i^T and V-RX V_j^R, the social relationship tightness is calculated as

$$\delta_{ij}=(corr(p_i,p_j)+1)/2. \tag{13}$$

We have $p_i\sim P_i(p)$ and $p_j\sim P_j(p)$, where P_i and P_j are the estimated correlative PDFs based on (12). δ_{ij} varies from 0 to 1, i.e., $\delta_{ij}\in[0,1]$.

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C. Physical and Social Layer Requirements

The physical and social layer requirements for D2D-V2V link establishment are defined in terms of connection probability and social relationship tightness. V-TX V_i^T and V-RX V_j^R are allowed to form a D2D-V2V pair V_{ij} if and only if both the connection probability and the social relationship tightness are no less than some predefined thresholds, which are denoted as η and δ, respectively. We define $\Gamma(x \mid x_0)$ as an indicator function of x such that $\Gamma(x \mid x_0) = 1$ if $x \geq x_0$, and otherwise, $\Gamma(x \mid x_0) = 0$. We denote ρ_{ij} as the physical-social score of V_{ij},which is calculated as

$$\rho_{ij} = \Gamma[F_{ij}(t) \mid \eta]\Gamma(\delta_{ij} \mid \delta)F_{ij}(t)\delta_{ij}. \tag{14}$$

ρ_{ij} varies from 0 to 1, i.e., $\rho_{ij} \in [0, 1]$. $\rho_{ij} = 0$ represents that V-TX V_i^T and V-RX V_j^R cannot form a D2D-V2V link.

III. Problem Formulation

In order to achieve effective content dissemination, both physical and social layer information are utilized to characterize the impacts of connection probability and social relationship tightness on the transmission rate. Hence, the objective function is defined as a weighted transmission rate, i.e., the transmission rate is weighted by the physical-social score. The optimization of the weighted transmission rate requires solving a joint peer discovery, power control, and channel selection problem, which involves a three-dimensional matching among V-TXs, V-RXs, and RBs. Thus, a three-dimensional $M \times M \times K$ matrix $\mathbf{O} = \{O_{i,j,k}\}$ is utilized to denote the set of peer discovery and channel selection strategies, in which $O_{i,j,k} {\in} \{0, 1\}$ is a binary variable. $O_{i,j,k}{=}1$ represents that V-TX V_i^T and V-RX V_j^R form a D2D-V2V pair V_{ij} by reusing RB C_k. The transmission power variable is defined as $P_{V_{ij},k}$. The joint peer discovery, power control, and channel selection problem is formulated as

$$\begin{aligned}
\max_{\{\mathbf{O}, P_{V_{ij},k}\}} \quad & \sum_{k=1}^{K}\sum_{j=1}^{M}\sum_{i=1}^{M} O_{i,j,k}\rho_{ij}r_{V_{ij},k} \\
\text{s.t.} \quad & C1: O_{i,j,k} \in \{0,1\}, \forall V_i^T \in \mathcal{V}_\mathcal{T}, V_j^R \in \mathcal{V}_\mathcal{R}, C_k \in \mathcal{C}, \\
& C2: \sum_{V_j^R \in \mathcal{V}_\mathcal{R}, C_k \in \mathcal{C}} O_{i,j,k} \leq 1, \forall V_i^T \in \mathcal{V}_\mathcal{T}, \\
& \quad \sum_{V_i^T \in \mathcal{V}_\mathcal{T}, C_k \in \mathcal{C}} O_{i,j,k} \leq 1, \forall V_j^R \in \mathcal{V}_\mathcal{R}, \\
& \quad \sum_{V_i^T \in \mathcal{V}_\mathcal{T}, V_j^R \in \mathcal{V}_\mathcal{R}} O_{i,j,k} \leq 1, \forall C_k \in \mathcal{C}, \\
& C3: 0 \leq P_{V_{ij},k} \leq P_{max}, \forall V_i^T \in \mathcal{V}_T, V_j^R \in \mathcal{V}_R, C_k \in \mathcal{C}, \\
& C4: r_{V_{ij},k} \geq r_{min}, \forall V_i^T \in \mathcal{V}_T, V_j^R \in \mathcal{V}_R, C_k \in \mathcal{C}, \\
& C5: r_{k,i} \geq r_{min}, \forall V_i^T \in \mathcal{V}_T, V_j^R \in \mathcal{V}_R, C_k \in \mathcal{C}.
\end{aligned} \tag{15}$$

Constraints $C1$ and $C2$ ensure that each V-TX can be paired with at most one V-RX and vice versa, while each RB can be reused by at most one D2D-V2V pair and vice versa. $C3$ specifies the transmission power constraint. $C4$ and $C5$ ensure that the QoS requirements of both D2D-V2V links and cellular links should be guaranteed simultaneously.

IV. A Price-Rising based Iterative Matching Algorithm

In this section, a price-rising based iterative matching algorithm is proposed to solve the joint optimization problem formulated in (15). Firstly, we introduce how to reduce matching dimensionality and how to establish preference lists based on the weighted transmission rate. Then, the details of the proposed price-rising based iterative matching algorithm is presented. Finally, we analyze the theoretical properties and discuss the relevant implementation details.

A. Matching Dimensionality Reduction and Preference Establishment

The problem (15) is NP-hard due to the combinatorial nature. To provide a tractable solution, matching dimensionality is reduced to simplify the original three-dimensional matching problem. We combine one V-RX and one RB to form a V-RX-RB (VR) combination. Since there are M V-RXs and K RBs, the set of $M{\times}K$ VR combinations is denoted as $\mathcal{VR}{=}\{VR_{jk}\}_{j=1,k=1}^{j=M,k=K}$. Hence, we transform the original three-dimensional matching into a two-dimensional matching which involves M V-TXs on one side and $M{\times}K$ VR combinations on the other side. The two-dimensional matching is defined as follows.

Definition 1: A matching Ψ is a one-to-one correspondence $\mathcal{V}_\mathcal{T} \cup \mathcal{VR} \to \mathcal{V}_\mathcal{T} \cup \mathcal{VR} \cup \{\emptyset\}$, and $\Psi(i) = VR_{jk}$ represents that V-TX V_i^T is matched with the combination VR_{jk}.

When $\Psi(i) = VR_{jk}$, for $\forall V_{i'}^T \in \mathcal{V}_\mathcal{T}$, $\Psi(i') = \{\mathcal{VR} \setminus \{VR_{jk}\}\} \cup \{\emptyset\}$. The matching Ψ is stable when there exists no V-TX-VR pair consisting of V_i^T and VR_{jk} that are not paired with each other but prefer each other to be their partner under matching Ψ, i.e., *blocking pair*.

In the two-dimensional matching, M V-TXs and MK VRs are paired with each other based on the preference lists. The preference of V-TX V_i^T towards VR combination VR_{jk} is modeled as the maximum achievable weighted transmission rate under the matching $O_{i,j,k} = 1$, which can be obtained by solving the following power control problem:

$$\begin{aligned}
\max_{\{P_{V_{ij},k}\}} \quad & \rho_{ij}r_{V_{ij},k} \\
\text{s.t.} \quad & C1: 0 \leq P_{V_{ij},k} \leq P_{max}, \\
& C2: r_{V_{ij},k} \geq r_{min}, \\
& C3: r_{k,i} \geq r_{min}.
\end{aligned} \tag{16}$$

The above problem can be easily solved by using standard convex optimization. After obtaining the preference of V_i^T towards any $VR_{jk} \in \mathcal{VR}$, the preference list of V_i^T is established by sorting all of VR combinations in a descending order according to the achievable maximum weighted transmission rates.

B. Price-Rising based Iterative Matching

After obtaining the preference lists of V-TXs, a price-rising based iterative matching algorithm is proposed to match V-TXs, V-RXs and RBs. The price rising strategy is employed to resolve the contention when multiple V-TXs prefer to be

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matched with the same V-RX or RB. The proposed algorithm is briefly described as follows.

In the initial step, each VR combination is assigned with a *virtual price* to reflect its matching cost for V-TXs. The initial value of the virtual price is set as zero. We denote $\mathcal{PR}$=$\{PR_1, \cdots, PR_j, \cdots, PR_M\}$, $\forall V_j^R \in \mathcal{V}_\mathcal{R}$ and $\mathcal{PC}$=$\{PC_1, \cdots, PC_k, \cdots, PC_K\}$, $\forall C_k \in \mathcal{C}$ as the price sets of V-RXs and RBs, respectively. Then, $\mathcal{PV}$=$\{PV_{jk}\}_{j=1,k=1}^{j=M,k=K}$ is denoted as the set of prices corresponding to VR combinations, where PV_{jk} is the sum of V-RX V_j^R's price PR_j and RB C_k's price PC_k.

In each iteration, V-TXs that have not been matched with any VR combination propose to their most preferred VR combination in updated preference lists based on their payoffs, which is calculated as the difference between the achievable maximum weighted rate and the current matching cost of the VR combination. A stable matching is formed if any V-RX or RB receives request from only one V-TX. Otherwise, contention arises when more than one V-TX send requests to the same V-RX or RB. Let $\mathcal{B}$ denote the set of V-RXs and RBs that receive multiple requests. Then, the V-RXs or RBs in $\mathcal{B}$ can raise their virtual prices with a step of e, which depends on the minimum value of the differences between any two neighboring preferences. Accordingly, V-TXs that compete for the same V-RX or RB have to update their preference lists based on the current virtual prices of VR combinations. The price rising process terminates when there remains only one V-TX.

In the final step, the algorithm ends when either all of the V-TXs have been matched if $M \leq K$, or all of the RBs have been matched if $K \leq M$.

C. Property Analysis and Implementation

The following properties of the proposed algorithm can be easily proved according to [36], [37]. In particularly, the proof of convergence is very similar to the proof of Theorem 1 in [38] (page 20, Appendix B). Interested readers can refer to it and references therein for more details.

Theorem 1: The proposed price-rising based iterative matching algorithm converges to a stale matching within finite iterations.

Theorem 2: The content dissemination matching Ψ is weak Pareto optimal for V-TXs.

In preference establishment process, the computational complexity for each V-TX to acquire the preferences is $\mathcal{O}(MK)$, and to establish the preference list is $\mathcal{O}(MK\log(MK))$. Furthermore, the computational complexity of the proposed algorithm is $\mathcal{O}(M^{N_l})$ when $M \geq K$ and $\mathcal{O}(KM^{N_l})$ when $K \geq M$, where M^{N_l} is the required iterations of the price rising process [39].

Our work complies with the future hierarchical computing architecture, in which both centralized and network-edge intelligence can be combined to support applications with diverse QoS requirements. Some delay-tolerant tasks with high computing demands such as social relationship estimation can be processed by the centralized computing infrastructure, while delay-sensitive tasks such as connection probability estimation can be executed locally without going through the delay-prone backhaul links.

TABLE I: Simulation Parameters.

Simulation Parameter	Value
Cell radius	500 m
Length and width of road segment	100 m, 10m
Distance from the base station to the road segment	100 m
Max D2D-V2V transmission distance L	100 m
Pathloss exponent α_c, α_v, α_{cv}, α_{vc}	3, 3.5, 4, 3
Max V-TX transmission power P_{max}	500 mW
Cellular transmission power P_k	200 mW
Noise power N_0	-110 dBm
Number of V-TXs and V-RXs M	$1 \sim 6$
Number of RBs and CUEs K	$1 \sim 6$
Vehicle speed	$\leq$ 50km/h
QoS requirement r_{min}	0.5 bit/s/Hz

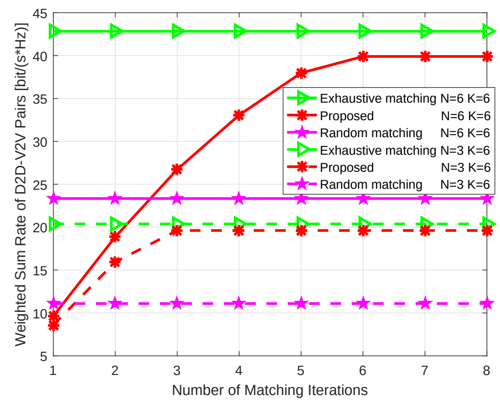
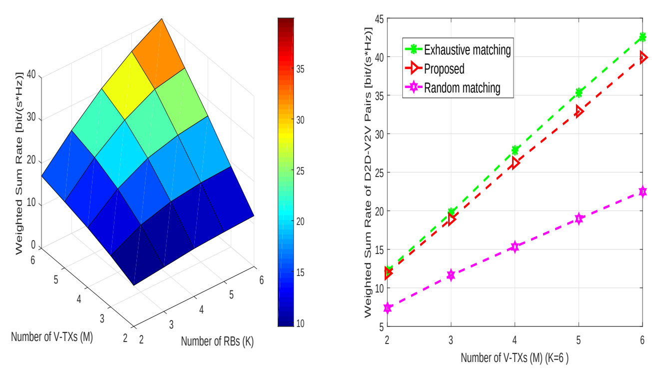


Fig. 3: Weighted sum rate of D2D-V2V pairs versus number of matching iterations $((\delta = 0.5, \eta = 0.5))$.

V. Simulation Results



(a) (b)

Fig. 4: The weighted sum rate performance of D2D-V2V pairs: (a) weighted sum rate versus different numbers of V-TXs and RBs; (b) weighted sum rate versus different numbers of V-TXs. $(\delta = 0.5, \eta = 0.5)$

In this section, the proposed algorithm is compared with exhaustive and random matching algorithms, which are utilized as the upper and lower performance bounds, respectively. The

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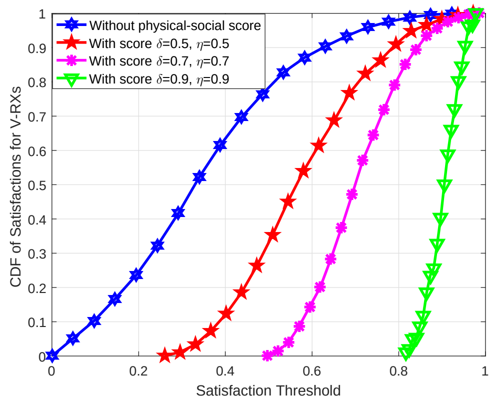

Fig. 5: The matching satisfaction of V-RXs versus different satisfaction thresholds.

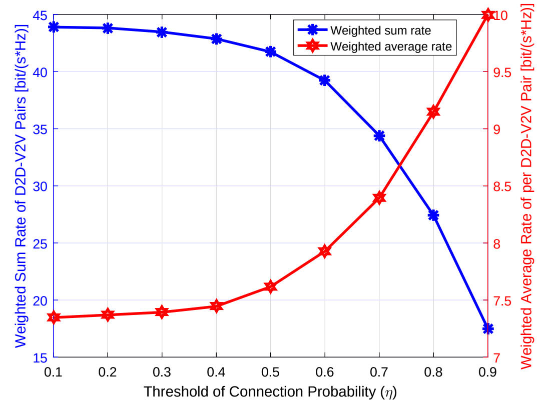

Fig. 6: The relationship between weighted sum rate of D2D-V2V pairs and the weighted average rate per D2D-V2V pair (N=6, K=6).

exhaustive matching algorithm searches through all of possible combinations to find the optimum solution. We consider one unidirectional lane of a road segment, in which two lanes with bidirectional vehicular traffic exist. Table I presents the simulation parameters [14], [16].

Fig. 3 shows the convergence performance of the proposed algorithm. The numbers of V-TXs, V-RXs and RBs have an obvious impact on the convergence speed, i.e., more iterations are required when K and M increase. Nevertheless, the proposed algorithm converges in only a few iterations and approaches the exhaustive matching algorithm. For instance, given $K = 6$, the proposed algorithm takes 3 and 6 iterations to converge when $M = 3$ and $M = 6$, respectively.

Fig. 4 (a) shows the weighted sum rate of V2V pairs with different numbers of V-TXs and RBs. It is observed that the sum rate performance increases along with the numbers of both V-TXs and RBs. When the number of RBs is fixed, adding more D2D-V2V pairs can contribute to higher sum rate performance due to proximity gain and spectrum reusing gain. On the other hand, since more D2D-V2V links can be supported by increasing the number of RBs, the overall network can benefit from diversity gain by exploring D2D-V2V links with longer connection time and higher preference similarity. Fig. 4 (b) compares the proposed algorithm with both the upper and lower performance bounds. It is observed that the performance achieved by the proposed algorithm is approximate to the optimum performance and significantly outperforms that of the random matching algorithm. For instance, the proposed algorithm can achieve up to 93.76% of the optimal performance and outperforms the random performance by 77.32%, when $M = 6$, $K = 6$.

Fig. 5 shows the matching satisfaction of V-RXs, which is defined as the CDF of the physical-social score. The impacts of physical-social score on V-RX satisfaction are evaluated by varying the thresholds of connection probability and social relationship tightness. It is observed that the satisfaction performance increases along with the thresholds. This is due to the fact that physical-social score is dramatically improved by allowing V-TXs and V-RXs with longer connection time and stronger social relationship tightness to form D2D-V2V pairs.

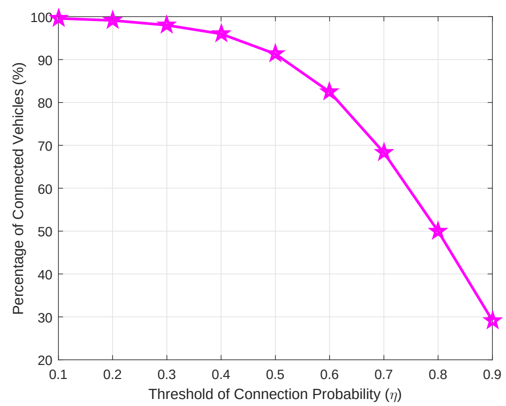

Fig. 7: Percentage of connected vehicles versus the threshold of connection probability η (N=6, K=6).

Fig. 6 shows the relationship between the weighted sum rate and the weighted average rate per D2D-V2V pair. The threshold of social relationship tightness δ is set as 0.7, and $M = K = 6$. When the threshold of connection probability η increases, the weighted average rate per D2D-V2V pair is improved at the expenses of the weighted sum rate. The reason is shown in Fig. 7, which demonstrates that percentage of connected vehicles decreases significantly as η increases. The weighted average rate gain is not enough to compensate for the sum rate loss caused by lower percentage of connection.

VI. Conclusion

In this paper, we investigated the content dissemination problem in D2D-V2V based IoV networks. Both the physical and social layer information in terms of connection probability and social relationship tightness were employed to solve the formulated joint peer discovery, power control, and channel selection problem. In particularly, we modeled the headway distance of vehicles as a Wiener process and estimated the connection probability of V2V pairs by exploiting Kolmogorov equation. The social relationship tightness was measured by

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employing BNL based on the real-word social big data collected from Sina Weibo and Youku. Then, a price-rising based iterative matching algorithm was proposed to maximize the sum rate of D2D-V2V pairs weighted by physical-social scores under the QoS constraints of both cellular and D2D-V2V links. The proposed algorithm was compared with two heuristic algorithms, and its effectiveness and superiority in improving sum rate and content satisfaction were validated through numerical results. In the future, we will consider the multi-hop D2D-V2V scenarios and study the joint optimization of content caching and dissemination.

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