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SPATH: Finding the Safest Walking Path in Smart Cities

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***Abstract*—Given the fact that more than 1 million crimes happened in U.S. every year, public safety becomes one of the most important concerns. Although many public safety related applications have been commercialized, how to guarantee safely walking to a destination, especially in an unfamiliar city is still challenging. To provide a safe walking navigation in smart cities, we design a novel application, SPATH (the Safest PATH). To support this service, wireless cameras, existing cellular infrastructure, and vehicles with underutilized computing resources are utilized to process and transmit surveillance videos, which can be viewed by users to check the current safety status of walking paths. Noting the long-distance transmission of a large volume of videos may cause network congestion, video summarizing technology, which is realized by utilizing the underutilized computing capability in vehicles, is applied to extract valuable information from a video file while effectively compressing its data size. Since the quality of service for this application is strongly correlated with the latency of delivering videos, we formulate a latency minimization problem by jointly considering the computing resource allocation and computing task assignment. A Fast Iterative Matching (FIM) is proposed with low complexity to effectively solve the optimization problem. Simulation results demonstrated the effectiveness and efficiency of our solution.**

***Index Terms*—Public safety, Smart city, Edge computing, Resource allocation.**

I. Introduction

Public safety is one of the most important concerns in the United States. According to the annual compilation of crimes reported by the law enforcement agencies, there were estimated 1,247,321 violent crimes committed in 2017. Moreover, there were estimated 319,356 robberies all the year round [1]. That is to say, nearly 38 robberies were reported every hour. In fact, most robberies occur in urban areas, especially at night. To improve public safety in cities, technology companies have already taken steps to design safety related applications. Recently, Mobile Software AS designs a new application, bsafe [2], which allows a user to add contacts as the guardians. When an imminent danger is perceived, a user can activate this application, which automatically sends alert to the recorded guardian. Similarly, Safe Apps Ltd. launches a StaySafe [3], which involves a new safety feature, called timed sessions. A user can set check-in intervals as their estimated session time. Once the user misses the session time deadline, this application will notify the corresponding contacts. However, all those applications are the post-crime services. Thus, how to offer a pre-crime warning is still an open problem.

Open crime dataset is considered by many researchers recently to identify the safest and shortest path for users [4]–[7]. In [4], Galbrun et al. utilize a crime probability model based on the existing crime data to measure the safety status of a walking path. Given historical crime locations, the estimated density of crime at a point can be quantified with Gaussian Kernel Density Estimation (KDE). Then, the estimated crime density of a walking path can be measured by aggregating crime occurring points on walking path. Goel et al. improve Galbrun's model in [5]. They design a safety model based on both the static and dynamic information. The static information is composed of crime related dataset belongs to different administrations. Dynamic information involves feedback received from users (crowdsourced). Users update the safety status of any point on their walking paths. Different from previous works, Garvey et al. [7] integrate pre-crime warning and post-crime support to design a novel safety application called PASSAGE. PASSAGE not only recommends safe paths to a user but also allows the user to share her current walking location with a friend.

However, the previous models suffer from the following limitations: (a) The historical crime data may be outdated; (b) The crime estimation model is not adapted well to small time scale; (c) Crowdsourced data cannot guarantee sufficient feedback; (d) User feedback based on personal experience is not accurate. In order to overcome these limitations, we propose to utilize street cameras with high resolution and wireless communication capability as the "remote eye" since street cameras has been widely deployed for many applications in smart cities. For example, Moscow has installed 160,000 outdoor cameras to support several public services such as trash removal, traffic management and crime monitoring [8]. Chicago has developed two public safety related programs, which has deployed over 32,000 cameras in the city in order to respond to traffic-related issues, monitor large crowds such as parades, and validate calls for fires or EMS [9].

Even though utilizing street cameras can overcome the limitations of previous design, long latency caused by the transmissions of large volumes of videos will impose restrictions on the use of these cameras. Edge computing provides

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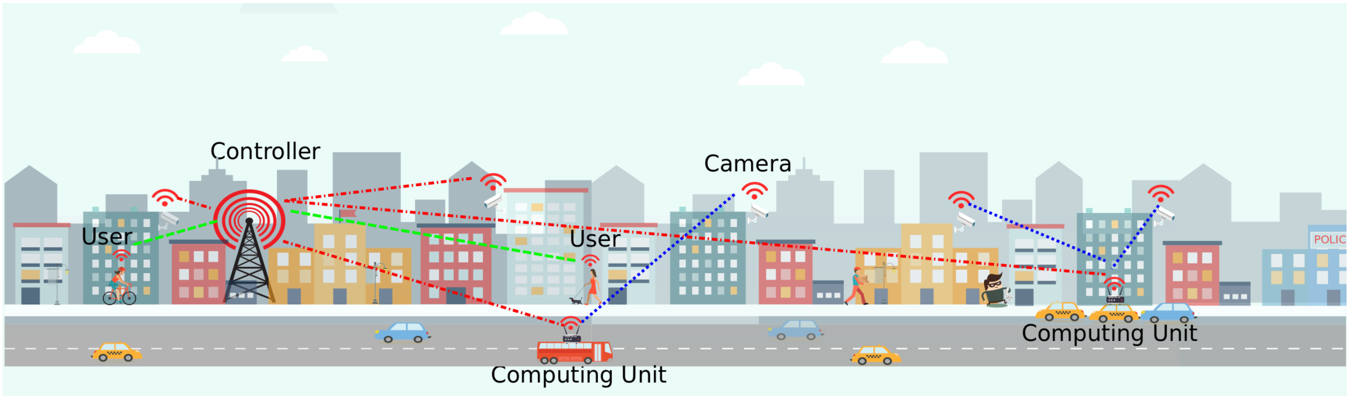

Fig. 1: System Architecture

a popular solution to this issue, which pairs data source with powerful edge servers [10]–[12]. Such servers are deployed at the proximity of data source to perform task computing or processing, data storage, and caching. For example, Rodrigues et al. [12] present a method by utilizing virtual machine migration and transmission power control to minimize service delay. As a result, their approach based on simultaneously lowering the time for transmission and the time for processing does reduce service delay significantly, particularly when the application involves with transmitting a large amount of data. Furthermore, in order to deal with communication and computing demands at edge more efficiently and conveniently, recent works propose a novel idea, which leverages vehicles as a service [13]–[18]. Apart from the edge computing characteristics, such as proximity to end users, computing, and storage, employing vehicles as a service distinguishes itself from dense geographical distribution of communication and computing devices and support for mobility [13]. In [15], Ding et al. propose a V-CCHN (Vehicular Cognitive Capability Harvesting Network) architecture. In this work, Cognitive Radio (CR) router enabled vehicles are employed to utilize harvested spectrum resources to opportunistically transmit large volume of data. Furthermore, with the built-in computing capability of CR routers, vehicles serve as edge cloud servers for local data processing and aggregation to solve network congestion problems and reduce long latency caused by the long-distance transmissions for large volumes of data.

Inspired by all previous works, we propose SPATH to effectively find the safest walking path in smart cities (as shown in Figure 1). The potential walking path of a user is divided into several road segments. To indicate the estimated safety status, each road segment is labeled by a numerical value, namely crime index. We utilize the historical crime data and kernel density estimation to estimate the crime index of each road segment. Wireless street cameras are employed to capture the street view of each road segment to provide fresh on-time street safety status. Based on the crime index, the captured videos are transmitted through the cellular infrastructure to users for identifying the safety status. It is reasonable to consider the slowly moving and parked vehicles (such as connected and autonomous vehicles) have plentiful and underutilized computing resources, which can be used to provide public services [13], [15], [19]. In order to handle the huge volume data of captured videos while avoiding potential network congestion, vehicles are treated as local computing units to summarize captured videos, which can effectively extract valuable information while reducing the data size of captured videos significantly [20]. The rationality of studying this problem is that utilizing the local computing units could reduce the latency for video delivery, which further improves the quality of safety. Thus, we formulate a latency minimization problem involving computing resource allocation and computing task assignment. Furthermore, we design a Fast Iterative Matching (FIM) algorithm with low complexity to effectively solve the latency minimization problem. The main contributions of this paper are listed as follows.

- A new application, SPATH, has been proposed to identify the safety status of a user's walking path. With the designed application, the videos of street cameras first are summarized on local computing units and then are transmitted to users for reviewing. We utilize vehicles with underutilized computing resources to reduce the latency for video analytics.
- Quality of safety for users is correlated with overall latency for video delivery and video analytics, and thus we formulate a latency minimization problem by jointly considering computing resource allocation and computing task assignment. Furthermore, due to the hardness of the original optimization problem, we develop a novel FIM algorithm, which can significantly reduce the complexity, to provide a suboptimal solution for the optimization problem.
- Simulation results show that the FIM algorithm outperforms other algorithms with low complexity. In addition, our proposed scheme can effectively reduce the latency.

The rest of this paper is organized as follows. Section II discusses the related work. Section III introduces system models. Section IV formulates the optimization problem. The mixed integer non-linear programming problem under multiple constraints is solved by a FIM algorithm in Section V. Performance of the proposed scheme is evaluated in Section VI. Finally, conclusions are drawn in Section VII.

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II. Related Work

In this section, we discuss the related work from two aspects, namely pre-crime warning applications and vehicle as a resource.

A. Pre-crime Warning Applications

Early works on the pre-crime warning applications, such as [4]–[7], are focused on utilizing historical crime data and crowdsourced feedbacks to assess the safety status. In [4], Galbrun et al. develop a crime probability model based on the historical crime data in Chicago and Philadelphia. They estimate the possible crime hot spots with Gaussian kernel density estimation. In order to measure the safety status of the navigation path, crime activity density is proposed, which is quantified by aggregating crime probability of each point on the walking path. Moreover, they design an algorithm to offer candidate paths for users with a different tradeoff between distance and safety.

By observing the drawbacks of the approach in [4], Goel et al. improve the safety model with two types of data, namely static and dynamic [5]. The static data is open data including historical crime data, road quality information, locations of police stations, and schedule of public transport, etc. Information in static data can be used to measure a navigation path is safe to walk or not. However, the static data may not accurately capture the actual situation as the information may be outdated. Therefore, the authors build a dynamic dataset to adapt to the information change. Dynamic data includes feedback from users in near real time, which is gathered in a crowdsourced manner. Users can report the safety status of any point on their walking path. Following the design of Goel et al., Mata et al. identify the crime level of the walking path with the official crime data and the useful information from online social media as in [6]. Criminal data repository is first built from tweets related to crime events. Then, the crime records are classified based on crime type, time, and location. Finally, a safe route is obtained from the estimation of crime rates.

Different from previous works, Garvey et al. [7] integrate pre-crime warning and post-crime service. In order to overcome the inaccuracy of the estimation of safety status, they develop the PASSAGE, a safety application. In [7], Garvey et al. also offer possible walking path of a user by applying estimation model of crime points and allows the user to add friends or relatives as the guardians, who receive the current location of the user.

B. Vehicle as a Resource

More recent studies focus on exploring better utilization of resources on connected and autonomous vehicles (CAVs). Vehicle as a resource is a novel idea leveraging vehicles to provide service of sensing, data storage, computing, and communications, etc. In [14], Zhang et al. propose a system architecture, where vehicles are service providers for smartphones. When infrastructure-based cloud does not have enough resource to support the service for users, residual computing in vehicles is allocated to accomplish mobile application offloading. In [15], [21], Ding et al. design a V-CCHN (Vehicular Cognitive Capability Harvesting Network) architecture, which utilizes CR routers enabled vehicles to handle the explosively growing wireless data traffic. The V-CCHN involves some new features, such as the capacity of reconfiguring agile communication interfaces to interoperate with other devices and mobility to realize data exchange within proximity, to fully exploit available vehicles. For more details of this architecture, readers are referred to [15].

To overcome the drawbacks of the previous works and better explore the benefits of residual communication and computing resources in vehicles, we propose SPATH, which transmits surveillance videos from street cameras to users to identify the safety status on walking paths and utilizes vehicles with underutilized computing resources as local computing units to summarize the videos to reduce the service latency.

III. System Architecture

In this section, we first present an overview of our proposed application, SPATH. Thereafter, communication, computing, and crime index model are explained in detail.

A. Architecture Overview

In this paper, we consider a scenario in Fig. 2. When a user launches the SPATH, the controller will activate the camera nodes to capture videos according to the user's walking path information and search for available vehicles near the activated camera nodes as the local computing units. Then, the controller gathers communication, computing, and safety related information (crime index) to make the task assignment decision and computing resource optimization. According to the control information, camera nodes transmit the pending videos to associated local computing units via appropriate communications technologies for video summarization analysis. Finally, the summarized videos are delivered to the user via the existing cellular infrastructure. The user could scan all the summarized videos to identify the safety status of the walking path. If the user considers the walking path is not safe enough, she can select alternative paths and make service request again. In this paper, we ignore the latency for request and control information message because of the small size of request and control information packet.

The architecture of our SPATH is shown in Fig. 2, which consists of four components: application, local computing units, camera nodes, and the controller.

1) Camera node: This can be a new wireless camera or a traditional street camera with communication radio interface and it can offload its captured videos to nearby computing units within the scope of a certain distance via D2D communications [22].

2) Local computing unit: This can be a moving or parking vehicle with sufficient computing and storage capability and it can perform video summarization task. Each vehicle can be matched with several camera nodes to summarize videos.

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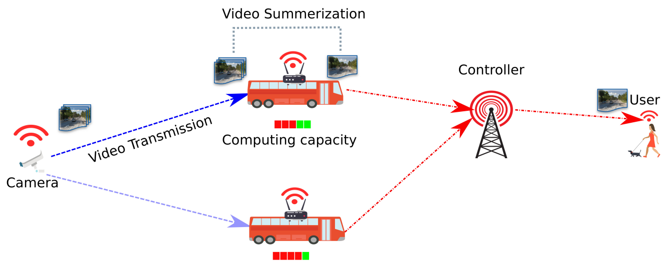

Fig. 2: Illustration of video summarizations and transmissions .

3) Controller: This is a static facility, which can be a base station or a roadside unit (RSU) or an access point (AP). It collects communication and computing information from camera nodes and vehicles. Based on the collected information and the crime index for each video task, it makes the task assignment decision and optimizes the computing resource.

4) Application: Application is installed on the user's mobile device. A user can use it to navigate, scan the summarized videos of the walking path, and make service request for alternative paths.

B. System Model

Denote the set of the camera nodes as $C = \{c_1, c_2, \cdots, c_i, \cdots, c_n\}$, the i-th camera node by c_i. Local computing units are indexed as $\mathcal{V} = \{v_1, v_2, \cdots, v_j, \cdots, v_m\}$, the j-th local computing unit by v_j. In this paper, we consider a widely used task model to describe video summarization task D_i, i.e., D_i=(α_i,β_i,$I(c_i)$), where α_i stands for required CPU cycle of the task D_i, and β_i denotes the data size of computing task D_i to be delivered toward the comping unit and $I(c_i)$ is the crime index of each task. Crime index indicates the significance of each task since the larger crime index, the higher probability of observing a crime incident. Then, we discuss communication, computing, and crime index model, which will be used in the subsequent development.

Communication Model: In this paper, we consider adopt orthogonal channels to support the data transmissions between camera nodes and local computing units. We assume camera nodes communicate with local computing units via D2D links and computing units transmit summarized videos to the user via cellular links. The data rate for the camera nodes offloading tasks to the associated computing units can be obtained as follows:

$$r_{i,j} = W_{i,j} \log_2 \left(1 + \frac{p_i h_{i,j}}{N_0}\right), \tag{1}$$

where $W_{i,j}$ indicates the allocated bandwidth and $h_{i,j}$ denotes the channel gain between the camera c_i and the computing unit v_j. Furthermore, p_i is the transmission power of camera node c_i, and N_0 is the noise power. We assume the mobility of local computing units is low and the offloading time is relative short, thus $h_{i,j}$ is a constant.

The transmission latency for transmitting the task D_i from camera node c_i to computing unit v_j is therefore given by

$$t_i^T = \frac{\beta_i}{W_{i,j} \log_2 \left(1 + \frac{p_i h_{i,j}}{N_0}\right)}. \tag{2}$$

Similar to previous works such as [23], this paper ignores the transmission latency of delivering summarized video from computing units to the user end, since the data size of summarized videos is much smaller than the original videos.

Computing Model: In this paper, we consider the difference of computing resource among local computing units and denote the computing resource of local computing units as $\mathcal{F}$ = $\{f_0, f_1, \cdots, f_j, \cdots, f_m\}$. We assume several camera nodes can share the computing resource of a local computing unit during the video summarization process. Thus, the computing time of task D_i can be written as

$$t_i^C = \frac{\alpha_i}{\kappa_{i,j} f_j}, \tag{3}$$

where $\kappa_{i,j}$ is the proportion of computing resource that computing unit v_j allocated to complete task D_i.

Crime Index Model: Crime index is a numerical value, which is used to label each road segment to indicate the estimated safety status. In this paper, crime index is measured based on the historical criminal activity probability and the estimated criminal activity probability. Thus, crime index is proportional to the probability that a crime incident on each road segment is observed. In general, the road segment with higher crime index are more dangerous because of the higher probability of observing a crime incident. For example, road segments in the urban area of Chicago [4] has a higher crime index since these road segments not only have been observed with a large number of criminal activities according to the historical data, but also have a high probability of observing a crime incident in the future based on the criminal activity probability estimation. In this paper, we apply Gaussian kernel density estimation to model the estimated criminal activity probability density. Given n points of crime locations are marked as $(q_{x,1}, q_{y,1}), (q_{x,2}, q_{y,2}), \cdots, (q_{x,n}, q_{y,n})$, the density of crime at a location (l_x, l_y) can be quantified as follows [4]:

$$f(l_x, l_y) = \frac{1}{n\sigma^2} \sum_{i=1}^{n} \frac{1}{2\pi} \exp\left(-\frac{\|l_x - q_{x,i}\|^2 + \|l_y - q_{y,i}\|^2}{2\sigma^2}\right), \tag{4}$$

where σ is a parameter that controls the smoothness of the density estimation, which can be determined by the Scott's rule [24]. We denote the set of the road segments as $\mathcal{S} = \{s_1, s_2, \cdots, s_k, \cdots, s_K\}$, the k-th road segments by s_k. Therefore, we can obtain the crime index of road segment s_k by

$$I(s_k) = -\log\left(\epsilon(1 - P_{s_k}^h) + (1 - \epsilon)\left(1 - P_{s_k}\right)\right), \tag{5}$$

where $P_{s_k} = \int_{e_{x,k}^L}^{e_{x,k}^U} \int_{e_{y,k}^L}^{e_{y,k}^U} f(l_x, l_y) \mathrm{d}l_x \mathrm{d}l_y$ is the estimated criminal activity probability and $e_{x,k}^L$,$e_{x,k}^U$,$e_{y,k}^L$, $e_{y,k}^U$ are edge positions for road segments s_k. $P_{s_k}^h$ denotes the historical criminal activity probability. ϵ is the weighting factor. Therefore, for

TABLE I: Symbols and definitions

Symbol	Definition
$\mathcal{C}$	Set of camera nodes
$\mathcal{B}$	Set of local computing units
$\mathcal{S}$	Set of road segments
D_i	Video summarization task for camera node c_i
c_i	i-th camera node
v_j	j-th computing unit
s_k	k-th road segment
p_i	Transmission power for camera c_i
$h_{i,j}$	Channel gain
f_j	Computing resource of local computing unit v_j
N_0	Noise power
α_i	Amount of the task
β_i	Data size of computing task
$W_{i,j}$	Bandwith
t_i^T	Transmission latency for video summarization task D_i
t_i^C	Computing latency for video summarization task D_i
$f(l_x, l_y)$	Probability density of crimes at location (l_x, l_y)
$I(s_k)$	Crime index of road segment s_k
ϵ	Weighting factor

each camera node c_i located in the road segment s_k, the crime index can be written as

$$I(c_i) = I(s_k), \tag{6}$$

which means all camera nodes located in the same road segment s_k has the same crime index. The main notations adopted in this paper are presented in Table I

IV. Problem Formulation

By leveraging communication, computing, and storage (CCS) capability, together with the crime index model proposed in the previous section, we design our SPATH by formulating a latency minimization problem considering computing task assignment and computing resource optimization. We first discuss several constraints for the latency minimization problem.

Task Assignment: To be specific, we define the integral decision matrix $\mathbf{x} = (x_{i,j})$ with $x_{i,j} \in \{0, 1\}$, where $x_{i,j} = 1$ indicates camera node c_i is associated with computing unit v_j for video summarization while $x_{i,j} = 0$ otherwise. Since we assume the captured video cannot be split, the camera node c_i can only be matched with one computing unit. This matching constraint can be written as follows:

$$\sum_{j\in\mathcal{V}} x_{i,j} \le 1. \tag{7}$$

Maximum Computing Power Limitation: In this paper, we consider the total amount of computing resource assigned to each task placed on computing unit v_j cannot exceed its limitation, that is,

$$\sum_{i\in\mathcal{C}} x_{i,j}\kappa_{i,j} \le 1. \tag{8}$$

Maximum Communication Channel Limitation: We consider each computing unit has limited available frequency sub-channels to communicate with camera nodes, we introduce the constraint as

$$\sum_{i\in\mathcal{C}} x_{i,j} \le Q. \tag{9}$$

Safety Guarantee: We consider that if a camera node is associated with a computing unit for video summarization, the status of this road segment is safest for a user since the user can obtain the fresh safety information. Thus, we redefine the crime index of selected camera node is $I(c_i) = 0$. In order to guarantee the safety of a user, we introduce the crime index requirement for a user's walking path as

$$\sum_{i\in\mathcal{C}} (1 - x_{i,j}) I(c_i) \le I_{th}. \tag{10}$$

Latency Minimization

Under the above setup, we pursue a latency minimization problem by jointly considering computing resource allocation and computing task assignment, which is formulated as

$$\mathbf{OPT}: \min_{\mathbf{x},\kappa} \sum_{i\in\mathcal{C}} x_{i,j}(t_i^T + t_i^C) \tag{11}$$
$$\text{s.t.} \quad \sum_{i\in\mathcal{C}} x_{i,j}\kappa_{i,j} \le 1, \quad \sum_{i\in\mathcal{C}} x_{i,j} \le Q, \quad \sum_{i\in\mathcal{C}} (1 - x_{i,j}) I(c_i) \le I_{th}, \quad \sum_{j\in\mathcal{V}} x_{i,j} \le 1, \quad x_{i,j} \in \{0, 1\}$$

It is clear that the proposed latency minimization problem is a mixed integer non-linear programming (MINLP) problem since it contains both binary variables $\mathbf{x}$ and continuous variables κ. In the next section, we adopt matching theory with low complexity to find an approximate solution to the proposed optimization problem because of the hardness of the original optimization problem.

V. Algorithm

In this section, a FIM algorithm is proposed to solve the optimization problem, since the MINLP optimization problem has a high complexity with the increasing number of camera nodes and computing units. The objective function can be rewritten as follows:

$$g(\boldsymbol{\kappa}, \boldsymbol{x}) = \sum_{i\in\mathcal{C}} x_{i,j}\left(\frac{\beta_i}{r_{i,j}} + \frac{\alpha_i}{\kappa_{i,j} f_j}\right). \tag{12}$$

We consider the original problem can be decoupled into two sub-problems, computing resource optimization problem and task assignment problem. Given $x_{i,j} = \hat{x}_i$, which means $x_{i,j}$ is fixed, the original latency minimization problem in (11) is converted as a computing resource optimization problem, which is a convex problem. Therefore, optimal solution, $\kappa_{i,j}^*$, of computing resource optimization can be obtained by adopting the Karush-Kuhn-Tucker (KKT) conditions. With the optimal solution, $\kappa_{i,j}^*$, obtained from the computing resource optimization problem, the latency minimization problem is converted as task assignment problem, which is an integer programming problem. Then, we adopt the matching theory to obtain the solution.

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A. Computing Resource Optimization

We consider the **OPT** with the following **OPT-RA** when $x_i = \hat{x}_i$, a fixed value.

$$\textbf{OPT-RA} : \min_{\boldsymbol{\kappa}} g(\boldsymbol{\kappa}, \hat{\boldsymbol{x}}) = \sum_{i \in C} \hat{x}_{i,j} \left(\frac{\beta_i}{r_{i,j}} + \frac{\alpha_i}{\kappa_{i,j} f_j} \right) \quad (13)$$
$$\text{s.t.} \quad \sum_{i \in C} \hat{x}_{i,j} \kappa_{i,j} \le 1$$

Therefore, the Hessian matrix of the **OPT-RA** can be derived as follows:

$$\mathbf{H} = \begin{bmatrix} \frac{\partial^2 g}{\partial^2 \kappa_{1,j}} & \frac{\partial^2 g}{\partial \kappa_{1,j} \partial \kappa_{2,j}} & \cdots & \frac{\partial^2 g}{\partial \kappa_{1,j} \partial \kappa_{n,j}} \\ \frac{\partial^2 g}{\partial \kappa_{2,j} \partial \kappa_{1,j}} & \frac{\partial^2 g}{\partial^2 \kappa_{2,j}} & \cdots & \frac{\partial^2 g}{\partial \kappa_{2,j} \partial \kappa_{n,j}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 g}{\partial \kappa_{n,j} \partial \kappa_{1,j}} & \frac{\partial^2 g}{\partial \kappa_{n,j} \partial \kappa_{2,j}} & \cdots & \frac{\partial^2 g}{\partial^2 \kappa_{n,j}} \end{bmatrix} \quad (14)$$

Further, we can obtain each specific element of the Hessian matrix is:

$$\frac{\partial^2 g}{\partial \kappa_{p,j} \partial \kappa_{q,j}} = \begin{cases} \frac{2\alpha_i}{\kappa_{i,j}^3 f_j} & \text{if } p = q \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

It is observed that all parameters in (15) are positive since $\frac{2\alpha_i}{\kappa_{i,j}^3 f_j} \ge 0$. We conclude that **OPT-RA** is convex because the Hessian matrix $\mathbf{H}$ is a positive definite matrix [25]. Since the constraints are linear, optimal solution of **OPT-RA** can be obtained with the KKT conditions.

We introduce the Lagrange function of **OPT-RA** according to the previous analysis, which can be written as follows:

$$L(\boldsymbol{\kappa}, \boldsymbol{\gamma}) = \sum_{i \in C} \hat{x}_{i,j} \left(\frac{\beta_i}{r_{i,j}} + \frac{\alpha_i}{\kappa_{i,j} f_j} \right) + \sum_{j \in \mathcal{V}} \gamma_j \left(\sum_{i \in C_j} \kappa_{i,j} - 1 \right), \quad (16)$$

where $\boldsymbol{\gamma} = (\gamma_1, \cdots, \gamma_m)$ are the Lagrange multipliers corresponding to the inequality constraints. Since Slater's condition holds for **OPT-RA**, then the KKT conditions provide necessary and sufficient conditions for optimality [26]. If κ^* and γ^* is the optimal point with zero duality gap, then the gradient for $L(\boldsymbol{\kappa}, \boldsymbol{\gamma})$ must vanish at point κ^*. Therefore, we can obtain:

$$\nabla \left(\sum_{i \in C} \hat{x}_{i,j} \left(\frac{\beta_i}{r_{i,j}} + \frac{\alpha_i}{\kappa_{i,j}^* f_j} \right) \right) + \sum_{j \in \mathcal{V}} \gamma_j^* \nabla \left(\sum_{i \in C_j} \kappa_{i,j}^* - 1 \right) = 0, \quad (17)$$
$$\gamma_j^* \left(\sum_{i \in C} \hat{x}_{i,j} \kappa_{i,j} - 1 \right) = 0.$$

Moreover, we can derive the optimal value of $\kappa_{i,j}^*$ form (17), which can be written as follows:

$$\kappa_{i,j}^* = \frac{\sqrt{\alpha_i}}{\sum_{i \in C} \sqrt{\hat{x}_{i,j} \alpha_i}}. \quad (18)$$

B. Task Assignment

After obtaining the optimal computing resource allocation, we develop an algorithm based on the matching theory [27] to solve the task assignment problem. Matching theory provides tractable solution to the problem of multiple agents in two distinct groups. Each agent wants to match with one or multiple agents in the opposite group. Mathematically, the many to one matching can be defined as follows.

***Definition** 1:* [28] Given two distinct set $\mathcal{M}$ and $\mathcal{W}$, a matching μ is a mapping function from $\mathcal{M} \cup \mathcal{W}$ into $2^{\mathcal{M} \cup \mathcal{W}}$, such that: $\mu(m_i) \subseteq \mathcal{W}$ and $|\mu(m_i)| \le 1$ for all $m_i \in \mathcal{M}$; $\mu(w_j) \subseteq \mathcal{M}$ and $|\mu(w_j)| \le N_j$ for all $w_j \in \mathcal{W}$, where N_j is the capacity of agent $w_j \in \mathcal{W}$; $\mu(m_i) = \{w_j\}$ if and only if $w_j \subseteq \mu(m_i)$ for all $(m_i, w_j) \in \mathcal{M} \times \mathcal{W}$

To better describe a matching, the preference lists of agents should be defined. Each agent holds a preference list to opposite group. All the actions, such as proposal, acceptance, and rejection are according to the preference list. In this paper, we establish each agent's preference list as follows.

1) Preferences of camera nodes: From the camera node's perspective, each camera node seeks the minimum of its transmission time to a local computing unit. Therefore, we propose a utility function for a camera node to form its preference list among computing units as follows:

$$\phi_{i,j}^C = \frac{\beta_i}{W_{i,j} \log_2 \left(1 + \frac{p_i h_{i,j}}{N_0} \right)}. \quad (19)$$

Thus, the preference list $\succ_{i,j}^C$ of camera node c_i can be constructed by using (19).

2) Preferences of computing units: The preference list of local computing units can be established according to the time cost of the video summarization for a matched camera node. The utility function for a local computing unit can be calculated as follows:

$$\phi_{i,j}^V = \frac{\alpha_i}{\kappa_{i,j} f_j}. \quad (20)$$

According to the above utility function, the preference list for computing unit v_j among camera nodes in the opposite group can be constructed as $\succ_{j,i}^V$.

C. Fast Iterative Matching (FIM) algorithm

We now introduce our proposed FIM algorithm, which is illustrated Algorithm 1. The FIM algorithm operates in an iterative way until achieving the stability. Initially, each camera node forms its preference list $\succ_{i,j}^C$. The whole FIM algorithm consists of two major phases: one is for matching and the other is for optimizing. At the beginning of matching in each round, each camera node c_i proposes to its most preferred computing unit v_j and removes v_j from its preference list $\succ_{i,j}^C$. When receiving c_i's proposal, v_j may face two conditions: either enough available communication channels for the transmission of c_i's video have been found or there are not enough available channels to support the c_i's video transmission. Computing nodes v_j first forms its preference list $\succ_{i,j}^V$ with the optimized computing resource, which can be calculated by (18). If v_j finds enough available communication channels to support the video transmission, it accepts the most preferred proposal and the matched camera node is removed from unmatched set C_{un}. If v_j does not find enough communication channels to support its video transmission, it discards the worst camera node and the discarded camera node is added to the unmatched set C_{un}. At the end of each round, if the constraint (10) is not satisfied,

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Algorithm 1 FIM Algorithm

Input: I_{min}, Q,f_j,$\succ_{i,j}^{C}$, C,$\mathcal{V}$,$l(c_i)$;
Output: Matching μ
Initialization;
Set $Q_j = Q$ for all v_j
Construct set C_{un},set C_{un}=C;

Matching;
for each $c_i \in C_{un}$ **do**
  Proposes to the first v_j in its preference list and remove v_j from $\succ_{i,j}^{C}$;
end for
for $v_j \in \mathcal{V}$ **do**
  Forms its preference list $\succ_{j,i}^{V}$ with the $\kappa_{i,j}^{*}$ by (18).
  if $Q_j > 0$ **then**
    v_j keeps the most preferred c_i^p among proposals;
    Removes c_i^* from C_{un}
    $Q_j = Q_j - 1$
  else
    v_j rejects the worst c_i^d and keeps the rest;
    Add c_i^d to C_{un}
  end if
end for
if constraint (10) is not satisfied **then**
  if $Q_j > 0$ for any v_j **then**
    Go back to **Matching**;
  else
    for $v_j \in \mathcal{V}$ **do**
      Discards c_i^d with the smallest crime index
      Go back to **Matching**;
    end for
  end if
end if

then camera nodes conduct next iteration. When there are no available communication channels for all computing units in the new iteration, all computing units discard the camera nodes with the smallest crime index. The matching and optimizing process iterates until safety related constraint (10) is satisfied, or all cameras are matched.

VI. Performance Evaluation

In this section, we evaluate the performance of the proposed scheme in three aspects: (i) The comparison among different task assignment schemes; (ii) The impact of available computing power; (iii) The impact of key parameters, such as the data size of videos and the bandwidth of communication channels. We introduce the simulation setup at first. Then extensive simulations are provided and analyzed.

A. Simulation Setup

We consider that the camera nodes are placed in the grid topology and a group of local computing units are randomly deployed. We assume the communication range of local computing units is up to 100 m. The data size and computing amount of tasks follow uniform distribution with a mean value of 5 MB and 1 Gigacycles, respectively [29]. The computing resources of computing units are distributed within the range [10, 20] GHz. The channel fading of the communication links is modeled by the complex normal distribution, $\mathcal{CN}(0, 1)$ [30].

The FIM, proposed in this paper, is compared with two task assignment schemes:

- Greedy assignment scheme: each camera node sends the proposal to match with the most powerful computing unit in its communication range. If a computing unit has enough communication channels to support all camera nodes, it will hold all video summarization task. If the received proposals have reached the limitation, the computing unit will accept the proposal according to the crime index. The computing resource allocation for each computing unit is according to (18).
- Random assignment scheme: camera nodes match with computing units randomly. If the communication limitation is reached, computing units are matched with camera nodes with respect to the crime index. The computing resource optimization is carried out according to (18).

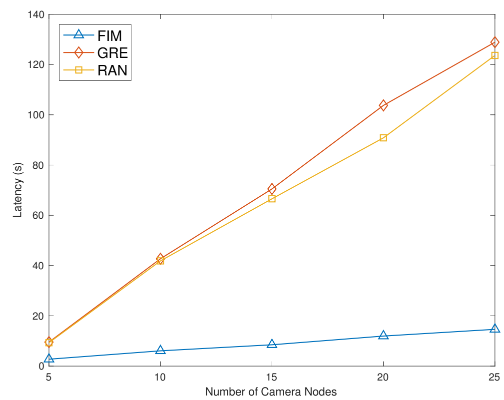

Fig. 3: The comparison between the proposed scheme with task assignment schemes with network size increasing.

B. Results and Analysis

Comparison among different task assignment schemes: The performance comparison among our FIM, greedy scheme, and random scheme is illustrated in Fig. 3. We let the number of camera nodes vary in [5, 25]. The density of the computing nodes is set to be a constant value with respect to the number of camera nodes. Results in Fig. 3 demonstrate that the proposed FIM achieves significantly better performance over the other two schemes. This is because the available number of computing units for each camera node is increasing with the network size increases. Therefore, FIM algorithm could exploit more benefits from the diverse choices. However, greedy and random schemes ignore the possible gain from the increasing number of computing units. Moreover, resource optimization for FIM can enhance the gain from diverse choices, since the matching choice is based on the result of

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resource optimization. Noticing that resource optimization can also achieve performance gain for greedy and random schemes. However, the benefit of resource optimization does not compensate for the loss of matching scheme.

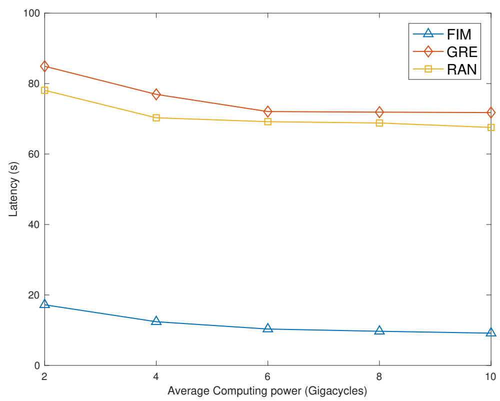

Fig. 4: Impact of available computing power.

Impact of available computing power: We further compare the performance of the FIM algorithm with two heuristic schemes under different available computing power. We set the number of camera nodes to 15 and the computing power in each local unit to be varying in [2, 10] Gigacycles. Figure 4 shows that FIM scheme achieves significantly higher performance gain over the other two schemes, particularly when the number of computing units is small. Noticing that FIM is introduced to adjust the matching choice according to available computing power when computing resource is insufficient, it is not surprising that a more significant performance gain can be observed when the computing power is smaller. Moreover, the latency of all schemes is reduced slowly when the number of computing units is large. The reason is that sufficient computing resource makes all task assignment schemes achieve less benefit with respect to the variation of computing resource.

Impact of data size : In Fig. 5, we investigate the latency of different task assignment schemes with respect to the varying data size of captured videos. The parameter settings are the same as those in Fig. 4 and the data size of the video varies within [1, 9] MB. The results shown in Fig. 5 demonstrate that three algorithms have the same relationship between latency and the data size of videos. The result shows that the larger of the data size, the longer of the latency. The result also demonstrates that the impact of the data size is evident, especially at large data size. The reason is that when the data size is large, FIM algorithm not only reduces the latency in terms of the choice of computing units but also achieves significant benefits from the transmissions of videos.

Impact of bandwidth: We also consider the impact of the bandwidth of communication channels. In this evaluation, The parameter settings are the same as those in Fig. 4 and the bandwidth of communication channels is set to the range [0.5, 2.5] MHz. The results shown in Fig. 6 demonstrate that the performance gaps of three task assignment schemes are narrowing along with the increasing of bandwidth. When the communication resource is sufficient, FIM can only achieve

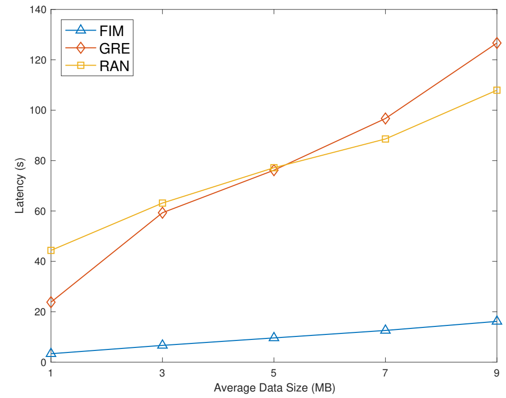

Fig. 5: Impact of data size

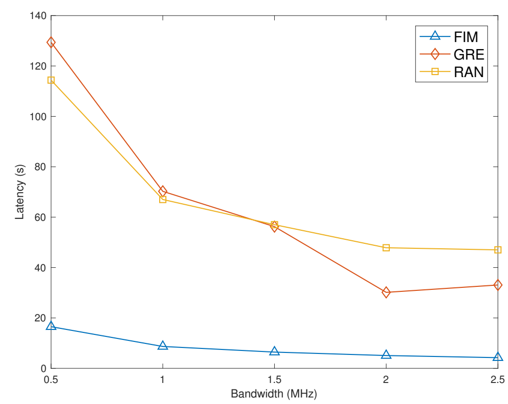

Fig. 6: Impact of bandwidth.

benefits from computing resource and the loss of greedy and random schemes is less for transmissions of videos. Fig. 6 also shows that the impact of bandwidth is more significant when bandwidth is small. The proposed FIM can achieve 85.6% better performance compared with random assignment scheme and 87.3% compared with greedy assignment scheme when bandwidth is 1 MHz. The reason is that when bandwidth is small, FIM can obtain more benefit from better communication channels.

VII. Conclusion

In this paper, we have proposed a safety application, SPATH, to handle safety issues in smart cities. We have utilized existing cellular infrastructures to transmit surveillance videos from street cameras to the users to identify the safety status. To handle the large volume of videos, we have leveraged the vehicles with underutilized computing resources as the local computing units to summarize videos. Since the quality of safety provisioning is strongly correlated with the latency of delivering the videos, we have formulated a latency minimization problem by jointly considering computing resource allocation and computing task assignment. Moreover, we have developed a Fast Iterative Matching (FIM) algorithm to solve the latency optimization problem. Simulation results show that our proposed scheme can effectively reduce the latency.

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