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Utility Based Scheduling for Multi-UAV Search Systems in Disaster-Hit Areas

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ABSTRACT Using micro or small unmanned aerial vehicles (UAVs) is a promising solution for search and rescue of missing persons who have disappeared during emergencies, such as natural disasters. In actual situations, the processing time of image data should be considered due to the wide variety of computing resources provided by UAVs. In addition, network connectivity and transmission speed could be unstable since communication infrastructure may have been damaged in disaster-hit areas. Thus, both the processing time of the acquired data and the data transfer time are critical in search and rescue missions. Unlike the solutions proposed in the past, we propose a scheduling method of multi-UAV search systems that takes into account both the processing time of image data and the data transfer time. We present a utility-based problem formulation that ensures continuously updating information while obtaining as many pieces of information as possible for a certain period. The simulation results indicate that the proposed scheduling method maximizes user utility and performs better than a conventional scheduling method in terms of user-centric evaluation metrics.

INDEX TERMS Unmanned aerial vehicle, search and rescue, scheduling, edge computing.

I. INTRODUCTION

The number of deaths and missing people due to natural disasters remains a serious problem in many countries. According to a report by the Centre for Research on the Epidemiology of Disasters [1], the average number of deaths and missing people due to natural disasters occurring worldwide, such as earthquakes, hurricanes, forest fires, and floods, from 2006 to 2015 was approximately 70,000. To reduce this number, a solution is to increase the number of rescue teams. The report by the Japan Ministry of Defense after the Great East Japan Earthquake suggests that it is necessary to secure manpower through guidelines regarding the concentration of rescue units in the immediate aftermath of a disaster. However, a huge budget to secure manpower and the risk of secondary damage in disaster-hit areas are problems to be solved [2].

Micro or small unmanned aerial vehicles (UAVs), also known as drones, are expected to solve the above problems in areas where humans and ground vehicles cannot easily enter, such as areas damaged by disaster. Recent technological advances have led to the emergence of smaller and cheaper UAVs, which can provide functions such as transporting relief supplies, acquiring data by using onboard sensors, and forming ad hoc wireless mesh network infrastructures in such isolated areas [3]–[5]. 'Acquiring data' in this paper means video based or image based remote sensing. Acquiring data is especially important because it is applicable to many use cases such as search and rescue missions and fire detection and surveillance. Since time is of the essence in such situations, UAVs need to acquire data as soon as possible. During the Great East Japan Earthquake, the number of deaths and missing people dramatically increased as time passed [6]. Surveillance using multiple UAVs has been receiving much attention for reasons such as increasing system reliability, robustness, and efficiency [7]–[11].

Previous studies [7]–[11] assumed that a user can obtain necessary information as soon as a UAV acquires data. However, the processing time of image data and data-transfer time should be taken into consideration because the time requirement for search and rescue in disaster-hit areas is strict.

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UAVs can be equipped with powerful computing resources such as GPUs or specialized hardware [12]. If available computing resources in the system are not powerful, it takes a long time to analyze multi-perspective image or video data for target recognition [13], [14]. Therefore, the system should work for a wide variety of available computing resources. Furthermore, since communication infrastructure may have been damaged in disaster-hit areas, network connectivity and transmission speed could be unstable.

Therefore, we propose a scheduling method of multi-UAV search systems that takes into account the processing time of image data and data-transfer time. With our proposed method, we perform both task allocation and scheduling among multiple UAVs. We also present a utility-based problem formulation that ensures continuously updating information while obtaining as many pieces of information as possible for a certain period. We show that the proposed scheduling method maximizes user utility, which is calculated from the efficiency of obtaining results from analyzed data and the interval of obtaining the results, through basic performance evaluation. We also present simulation results using three evaluation metrics from a user-centric viewpoint to verify the effectiveness of the proposed scheduling method against a benchmark conventional scheduling method.

The remainder of this paper is organized as follows. In Section II, we discuss related work. In Section III, we give an overview of the multi-UAV search system we considered in this study and the proposed scheduling method. In Section IV, we discuss the basic performance evaluation of our method in terms of user utility followed by simulation results in Section V. Finally, we conclude the paper in Section VI.

II. RELATED WORK

We now briefly discuss related work in the application of UAVs to disaster areas from both coverage and computing perspectives.

A. UAV APPLICATIONS IN DISASTER AREAS

Transporting relief supplies by using UAVs is very important since there is a possibility that humans and ground vehicles may not be able to easily enter disaster areas. Bamburry mentioned the ability of a UAV to deliver medical products to remote and hard-to-reach areas [16]. For example, in the devastating 2010 earthquake in Haiti, a UAV delivery system was used to deliver medicine to camps set up after the disaster [17].

UAVs can also acquire data by using onboard sensors. In the study by Wada *et al.* [18], Each UAV was provided with mobile optical sensors and image transmission modules they developed. An optical sensor, which is a combination of an infrared sensor and visible-light sensor, enables data acquisition even at night or in smoky disaster areas. After launch, a UAV executes auto flight by recognizing its positions and obtains the necessary video/image information. The UAV transmits the information to the server and shares it with users via the Internet.

UAVs also often work to form an ad hoc wireless mesh network infrastructure, which is called a flying ad hoc network (FANET) [19]. In 2016, Sánchez-García *et al.* aimed to provide connectivity for rescuers and disaster victims using UAVs [20]. They proposed Jaccard-based movement rules to define the best positions of UAVs for providing the best communication service to victims in an urban disaster scenario. They also compared several local search computational intelligence algorithms, such as simulated annealing, hill climbing, and random walk, for determining the best tactical UAV movements.

B. MULTI-UAV COOPERATION FOR AREA COVERAGE

Maza and Ollero conducted a pioneering study on cooperatively searching a given area to detect objects of interest by using UAVs [8]. They first determined the relative capabilities of each UAV based on factors such as flight speed, altitude required for the mission, sensitivity to wind conditions, and sensing width. They then divided the entire area by using a divide-and-conquer approach, taking into account the UAV's relative capabilities and initial locations. Finally, they set the waypoints of each UAV to minimize the number of turns needed along a zigzag pattern.

Zhao *et al.* in 2016 tackled the challenging problem of not only searching a target area for a lost target but also tracking the target [10]. At the tracking stage, each UAV maintains the desired distance with the target, coordinating the angular separation between neighboring UAVs to the same angle. If there is a shelter between the UAV and target, the target state is predicted from the target model with the former target information. At the searching stage, multiple UAVs divide the search region equally, which is determined by the target-loss duration and speed, then search for the target by using the method of shrinking annulus. They also proposed switching tactics between the tracking and searching stages.

In 2017, Hayat *et al.* proposed a multi-objective optimization algorithm to search for and plan paths for UAVs [21]. UAVs cooperatively search for a target, and soon after a UAV detects the target, the other UAVs take positions for relay chain formation between the detecting UAV and base station. This algorithm minimizes the mission-completion time, which includes the time to find the target and time to setup a communication path. They also compared three similar UAV search strategies but have different path planning in terms of the mission-completion time.

C. MULTI-UAV COOPERATION FOR COMPUTING

UAV applications in disaster areas require UAVs to handle intensive computation tasks such as image/video processing, pattern recognition and feature extraction. Computation offloading is very important since the computational power of a single UAV is limited.

1) INTER-UAV COOPERATION

Ouahouah *et al.* in 2017 proposed the use of an offloading mechanism among UAVs equipped with internet-of-thing (IoT) devices [22]. Each IoT task is partitioned into a set of sub-tasks that can be executed simultaneously among a cluster of UAVs. The sub-tasks are assigned to UAVs based on their power supply, resources in terms of memory and CPU computation, and their on-board IoT devices. Two solutions were proposed for computation offloading, i.e., energy-aware optimal task offloading and delay-aware optimal task offloading. The former maximizes the UAVs lifetime by selecting the UAVs with higher power supply. The latter reduces the response time by favoring the selection of UAVs with more resource capacities.

In 2018, Valentino *et al.* proposed an opportunistic and adaptive computational offloading scheme between UAV clusters [23]. A cluster head will broadcast a 'hello' message indicating their presence and available resources, then a local cluster sends an offloading request to the desired cluster head. The local cluster determines if it is better to do the task alone or to offload by estimating response time for doing the computational offloading and processing the given task through computing power, task size, bandwidth, and data rate of the wireless network.

2) EDGE COMPUTING

Edge computing has been proposed as an effective means of supplementing computational resources for UAVs [24], [25].

Motlagh *et al.* in 2017 demonstrated how UAVs can be used for crowd surveillance based on face recognition. Due to the computational overhead required by such a use case and given the limited power supply of UAVs, they carried out the offloading of video-data processing to a mobile edge-computing node. The results clearly indicated the benefits of computation offloading compared to the local processing of video data onboard UAVs in saving energy and quickly detecting and recognizing suspicious individuals in a crowd.

Messous *et al.* in 2017 tackled the computation offloading problem with three different devices: UAV, base station, and edge server, which carry out heavy computation tasks. They proved the existence of a Nash Equilibrium and designed an offloading algorithm that converges to the optimal point. Their cost function was defined as a combination of two performance metrics: energy and delay. They finally achieved better utility value using this offloading algorithm compared to computing on an edge server, base station, or drone.

III. PROPOSED SCHEDULING METHOD

In this paper, which is a full-paper version of an extended abstract presented at IEEE GCCE 2018 [15], we assume that UAVs are used for data acquisition using on-board sensors, that the UAVs cooperate with each other to cover a sensing region, and that the UAVs cooperate with an edge server to share the computing needs required for the disaster-relief application.

A. MULTI-UAV SEARCH SYSTEM OVERVIEW

1) SYSTEM MODEL

Figure 1 illustrates the multi-UAV search system model we considered for this study. The system consists of a user device (UD), multiple UAVs, and an edge server (ES), the roles of which are described as follows. The UD is the central operating entity in the system and operates all the UAVs and the ES; the UD determines flying routes and timing of UAVs and assigns workloads of computing sensor data to the UAVs and ES. The UD also works to forward sensor data received from the UAVs to ES and obtain computational results from both UAVs and the ES.

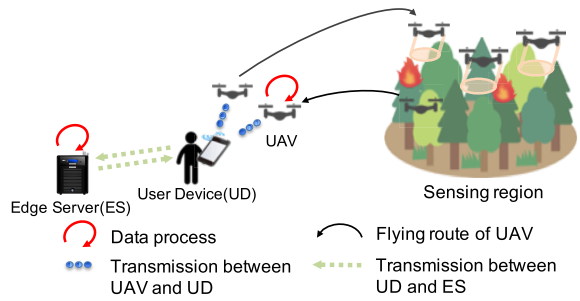

FIGURE 1. Diagram of multi-UAV search system.

Each UAV is operated by the UD and autonomously performs a task consisting of the following sub-tasks in a distributed manner: (i) Flying sub-task: flying between the initial position, at which the UAV can communicate directly with the UD, and the sensing region assigned to the UAV, (ii) Acquiring sub-task: acquiring data of the sensing region assigned to the UAV, (iii) Staying at the initial position and performing the following sub-tasks in parallel: (a) Analyzing sub-task: analyzing some of the acquired data with the computational power of the UAV and (b) Delegating sub-task: delegating the analysis of the rest of the data to the ES and (iv) Reporting sub-task: reporting the results obtained from the image-data analysis to the UD soon after it has been completed. Note that we assume that UAVs cannot perform any analysis while flying; computational resources of UAVs are fully used for flight control and data acquisition during the flight. Each UAV repeats all sub-tasks. We call one cycle of sub-tasks (i) to (iv) of a UAV as "one round." The ES is placed closely to the UD to perform the analysis of some of the image data received from the UAVs. Once the ES has completed the analysis, it reports the results to the UD.

2) SYSTEM FLOW

In our considered system, the task allocation/scheduling for UAVs is performed through the following steps:

(1) Check if there is one or more UAVs for which task allocation/scheduling has not been completed yet. If yes, go to step (2). Otherwise repeat step (1).

(2) Select one of the UAVs for which task allocation/scheduling have not been completed yet and label it as UAV $i (i = 1, 2, 3, \cdots)$, if step (1) is yes.

(3) Refer to the information about the task allocation/scheduling for UAVs $i-1, i-2, i-3, \cdots$, which were scheduled before UAV i.

(4) Perform the task allocation/scheduling of UAV i by using a scheduling method, which is described later.

(5a) Increment i to $i + 1$. Go back to step (1).

(5b) UAV i starts its operation based on the assigned tasks and will be added to the list of unscheduled UAVs after completing all sub-tasks mentioned in Section III-A1.

Note that steps (5a) and (5b) are executed in parallel. At step (4), the scheduling method requires some calculation time for task allocation/scheduling for UAV i. The calculation time depends on the complexity of the scheduling method. Therefore, the scheduling method should not be complicated. However, during the second or later round of the task allocation/scheduling for a UAV, the calculation can be done while the UAV is performing step (5b) because all the previous schedules before the UAV have been determined and the information of all the previous schedules are available. When the ES receives a computational task from a UAV via the UD, the ES places it into the waiting queue. The ES processes computational tasks in first-in first-out (FIFO) manner and reports the results to the UD immediately after finishing each computational task.

B. DESCRIPTION OF SCHEDULING METHOD

For simplifying our theoretical discussion, we first assume the system model shown in Figure 2, in which sensing sections are placed on a one-dimensional line and their sizes are identical. Sensing sections are assigned to UAVs from the one closest to the initial position and only an image is acquired at each sensing section. These assumptions allow us to simply consider the task allocation/scheduling for UAVs as setting the number of images acquired and images processed by them. We also assume that, if the computing resource of the ES or the communication channel of the UD is still used by previously scheduled UAVs (UAVs $1, 2, \cdots, i-1$), UAV i has to wait in FIFO manner until their operations are completed. This also means that the operation of UAV i does not affect those of the previous UAVs (UAVs $1, 2, \cdots, i-1$).

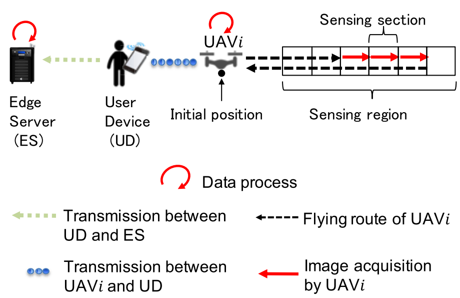

FIGURE 2. System model for problem formulation.

1) UTILITY FUNCTION

This section presents the mathematical development of the utility function of UAV i, U_i, which is given as

$$U_i = \frac{\eta^i}{\Delta t^i}, \tag{1}$$

TABLE 1. Definition of notation.

Notation	Description	Dimension
N^i	No. of images acquired by UAV i	(no. of images)
N_u^i	No. of images processed by UAV i	(no. of images)
N_e^i	No. of images delegated from UAV i to ES	(no. of images)
D	Distance between initial position and left-end of sensing block	(m)
d	Size of each sensing section	(m)
v^i	Flying speed of UAV i	(m/s)
T_g	Image-acquisition time per sensing section	(s)
$T_{u,d}^i(N^i, N_u^i)$	Transmission-waiting time from UAV i to UD	(s)
$T_{d,e}^i(N^i, N_u^i)$	Transmission-waiting time of UAV i's data from UD to ES	(s)
$T_e^i(N^i, N_u^i)$	Processing-waiting time at ES	(s)
$\mu_{u,d}$	Transmission speed from UAV i to UD	(no. of images/s)
$\mu_{d,e}$	Transmission speed from UD to ES	(no. of images/s)
P_u^i	Processing speed of UAV i	(no. of images/s)
P_e	Processing speed of ES	(no. of images/s)

where η^i denotes the efficiency of obtaining results from analyzed data and Δt^i is the interval of obtaining the results. Specifically, the acquisition efficiency and acquisition interval are respectively formally defined as

$$\eta^i = \frac{N^i}{t_{\text{fin}}^i - t_{\text{start}}^i} \tag{2}$$

$$\Delta t^i = t_{\text{fin}}^i - t_{\text{fin}}^{i-1} \quad (t_{\text{fin}}^0 = 0, t_{\text{fin}}^i \geq t_{\text{fin}}^{i-1}), \tag{3}$$

where N^i denotes the number of images acquired by UAV i, t_{start}^i is the flight start time of UAV i, and t_{fin}^i is the time when the processing of N^i images is completed. The U_i defined in (1) suggests that, as the acquisition efficiency and interval become higher and shorter, the system works better for users. The reason this is reasonable is because, in surveillance scenarios, users expect to obtain as many pieces of information as possible during a certain period, while more updated information would be more valuable to them.

2) UTILITY MAXIMIZATION

This section discusses the problem formulation of the proposed scheduling method. Table 1 lists the notations we use. In this table, N^i, N_u^i, and N_e^i are variables. The problem formulation is described below by using these notations:

$$\arg\max_{N^i, N_u^i} \; U_i = \frac{\eta^i}{\Delta t^i} = \frac{N^i/(t_{\text{fin}}^i(N^i, N_u^i) - t_{\text{start}}^i)}{t_{\text{fin}}^i(N^i, N_u^i) - t_{\text{fin}}^{i-1}} \tag{4}$$

$$\text{s.t. } N_{\text{MIN}}^i \leq N^i, \tag{5}$$

where N_{MIN}^i means that UAV i has to acquire at least N_{MIN}^i images so as not to complete its task earlier than the previous UAV, UAV $i-1$: $t_{\text{fin}}^i \geq t_{\text{fin}}^{i-1}$. N^i and N_u^i must be determined so that U^i is maximized subject to the constraint in (5).

The t^i_{fin} in (4) is given as

$$t^i_{\text{fin}}(N^i, N^i_u) = t^i_{\text{start}} + \frac{2}{v^i}(D + \sum_{j=1}^{i-1} N^j d) + N^i(T_g + \frac{d}{v^i}) + \max(\frac{N^i_u}{P^i_u}, T^i_{u,d}(N^i, N^i_u) + \frac{N^i_e}{\mu_{u,d}} + T^i_{d,e}(N^i, N^i_u) + \frac{N^i_e}{\mu_{d,e}} + T^i_e(N^i, N^i_u) + \frac{N^i_e}{P_e}). \tag{6}$$

Eliminating N^i_e from (6) and using $N^i = N^i_u + N^i_e$, $t^i_{\text{fin}}(N^i, N^i_u)$ becomes a function of two variables, N^i and N^i_u. According to (6), $t^i_{\text{fin}} - t^i_{\text{start}}$ is equal to the sum of the flight time, transmission time, and processing time of UAV i. The second and third terms on the right side of (6) represent the flight time outside the sensing range of UAV i and the sum of the image-acquisition and flight times within the sensing range assigned to UAV i, respectively. The max function of the fourth term on the right side of (6) is the processing time of N^i images, which is equal to the longer image-processing time at UAV i or the total time required for image transmission from UAV i to the ES and the image processing at the ES. The $T^i_{u,d}(N^i, N^i_u)$, $T^i_{d,e}(N^i, N^i_u)$, and $T^i_e(N^i, N^i_u)$ on the right side of (6) are waiting times for UAV i. As we mentioned above, if previous UAVs (UAVs $1, 2, \cdots, i-1$) are still using the communication channel of the UD or the computational resource of the ES, UAV i has to wait for a certain time until all the transmission and processing tasks have been completed. That is, t^{i-1}_{fin}, which is the time when processing N^{i-1} images acquired by UAV $i-1$ is finished, is not affected by the operation of UAV i and can be considered a constant value in the task allocation/scheduling for UAV i. Since the size of output data obtained after processing at UAVs and the ES is quite small, we assumed that the transmission time of the output data is negligible.

The N^i_{MIN} in (5) is the specific value of N^i that satisfies the following condition:

$$\arg\min_{N^i, N^i_u} \; t^i_{\text{fin}}(N^i, N^i_u) \tag{7}$$

$$\text{s.t. } t^i_{\text{fin}}(N^i, N^i_u) \geq t^{i-1}_{\text{fin}}(N^i_u \in \mathbb{N} \mid 0 \leq N^i_u \leq N^i). \tag{8}$$

Suppose that N^i_u is determined to minimize $t^i_{\text{fin}}(N^i, N^i_u)$ for a given N^i. For such N^i_u, N^i_{MIN} is the minimum integer among possible values of N^i that satisfy (8). By setting N^i_{MIN} as long as N^i_u is chosen to satisfy $0 \leq N^i_u \leq N^i$, the optimal N^i in (4) can be determined among the possible values of N^i that satisfy $U^i(= \frac{\eta^i}{\Delta t^i}) > 0$.

The solution to the utility maximization problem in (4) with constraint in (5) is discussed in detail in Appendix.

C. REQUIREMENTS OF SCHEDULING FOR MULTI-UAV SEARCH SYSTEM

From a user-centric viewpoint, the scheduling of multi-UAV search systems should satisfy the four requirements described below.

- Robustness against the increase or decrease in number of UAVs: The number of UAVs may increase due to adding new UAVs to the existing UAV group or decrease due to UAV breakdown. If there are new UAVs, they are added to the group of the unscheduled UAVs in step (1) of the system flow mentioned in Section III-A2. If some UAVs break down on the way, task reallocation and rescheduling are performed for the UAVs that were planned to start operations afterwards. These UAVs are added to the group of the unscheduled UAVs in step (1) of the system flow.
- Applicability for the heterogeneity of UAVs: There are individual differences in the flying speed and the processing speed of each UAV. With our proposed scheduling method, such individual differences are considered using (6).
- Applicability for various processing capacities of UAVs and the ES: The computational performance of each UAV and the ES greatly depends on the machine capability. With the proposed method, it is possible to efficiently use the computing capacity of each UAV and the ES since $t^i_{\text{fin}}(N^i, N^i_u)$ in (6) is defined considering machine performance.
- Feasibility for extension to various geographical areas: There are many types of geographical areas in practical situations. As we discuss in Section V-A, our proposed scheduling method is applicable for two-dimensional models by extending the one-dimensional model shown in Fig. 2. It is obvious that extension to three-dimensional models can also be considered, though the details are not presented in this paper.

IV. BASIC PERFORMANCE EVALUATION

We now present the results of utility-maximization-based scheduling using a simulation scenario.

A. SIMULATION SCENARIO

We consider a surveillance scenario in which a rescue team uses the multi-UAV system illustrated in Figure 1 to find missing people in an area where humans and ground vehicles cannot easily enter. We assumed the simple model illustrated in Figure 2, in which sensing sections are placed on a one-dimensional line and their sizes are identical, to present the problem formulation. Our simulation adopted the proposed scheduling method described in Section III-B and performed every step of the system flow described in Section III-A2. We compared the proposed method with a conventional scheduling method (referred to as the fixed method), which simply assigns a fixed number of sensing sections to each UAV uniformly [10]. With the fixed method, N^i_u is determined so that t^i_{fin} is minimized. In our basic

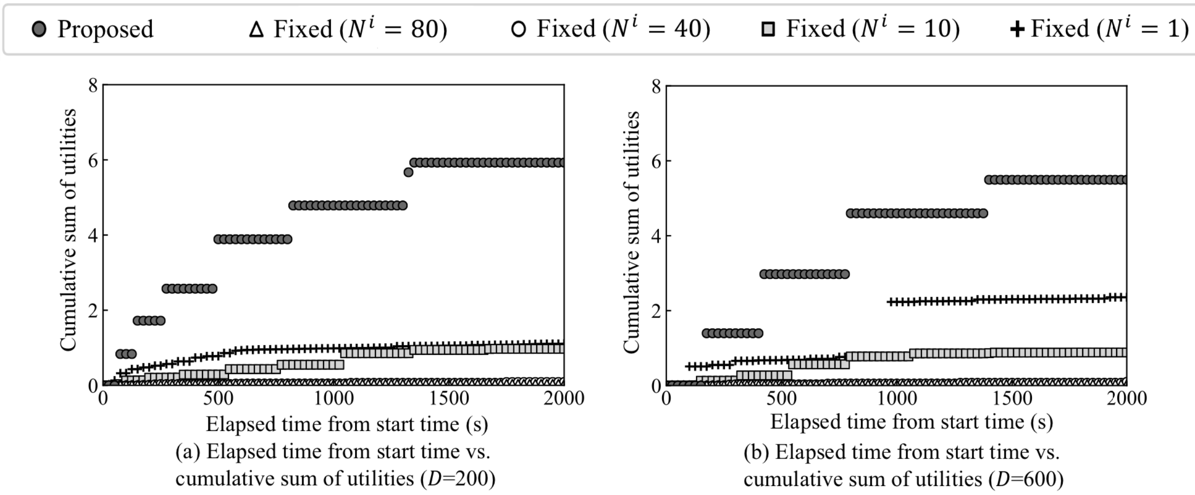

FIGURE 3. Cumulative sum of utilities. (a) Elapsed time from start time vs. cumulative sum of utilities ($D = 200$). (b) Elapsed time from start time vs. cumulative sum of utilities ($D = 600$).

evaluation, we assumed that the user cumulatively obtains U_i, which is defined by (1), every time UAV i finishes one round at t^i_{fin}. Then, we observed how the cumulative summation of U_i increases over time after the first UAV has started flying.

B. SIMULATION PARAMETERS

The parameters used in our simulation are listed in Table 2. Considering the realistic specifications of a recently commercialized UAV [26], we set the flying speed of UAVs to 15 m/s. The image size was set to 100 kbytes, which corresponds to that in the dataset called PASCAL VOC 2007 used in a previous study [27]. The times required for processing one image at the UAVs and ES were set corresponding to the time required for object recognition using CPUs and GPUs [27], respectively. As described in Section III-C, we need to consider the heterogeneity of UAVs from a user-centric viewpoint. Therefore, the flying speed of and number of images processed by UAVs were given by the normal distributions where the mean and deviation were μ and σ. We set $\sigma = 0.1\mu$ and the upper and lower limits to $\mu + 2\sigma$ and $\mu - 2\sigma$, respectively. The transmission rates of the communication channel from the UAVs to UD and from the UD to ES were set to 100 Mbps, which is similar to the effective throughput of IEEE802.11n [28].

TABLE 2. Simulation parameters.

Parameters	value
No. of UAVs (U)	5
Average flying speed of UAVs	15 m/s
Distance from initial position to left-end of sensing block (D)	200,600 m
Size of each sensing section (d)	5 m
Time required for acquiring one image	2 s
Transmission rate of communication channel	100 Mbps
Size of image	100 kbytes
Average processing speed of UAVs regarding no. of images per unit time ($\overline{P_u}$)	$\frac{1}{1.83}$
Processing speed of ES regarding no. of images per unit time (P_e)	$\frac{1}{0.198}$

C. RESULTS

Figures 3 (a) and 3 (b) plot the cumulative sum of utilities against elapsed time after start time with $D = 200$ and $D = 600$, respectively. We examine the fixed method with $N^i = 1, 10, 40$, and 80. As we see in the figures, the cumulative sum of utilities with both methods remains almost constant and then increases as time passes. The cumulative sum of utilities with the proposed method is the largest at any elapsed time, which suggests that the proposed method performs better than the fixed method in terms of the cumulative sum of utilities.

V. EVALUATION FROM USER-CENTIC VIEWPOINT

We discuss the three evaluation metrics we use to evaluate our proposed scheduling method from a user-centric viewpoint.

A. EXTENSION TO TWO-DIMENSIONAL MODEL

Before introducing the evaluation metrics, we introduce the two-dimensional model we use for the evaluation. The following two assumptions make our proposed scheduling method described in Section III-B easily applicable for two-dimensional models shown in Figure 4.

(1) Assuming a fan-shaped sensing region, split the region so that each sensing-section range is constant.

(2) Each UAV executes sensing on a zigzag line from the area closest to the center, such as in a previous study [8].

In Figure 4, the vertical width of each partition is d and the central angle of the sensing region is θ (rad). Then, the distances between each neighboring section is d for the direction opposite the center of the region, while those between each

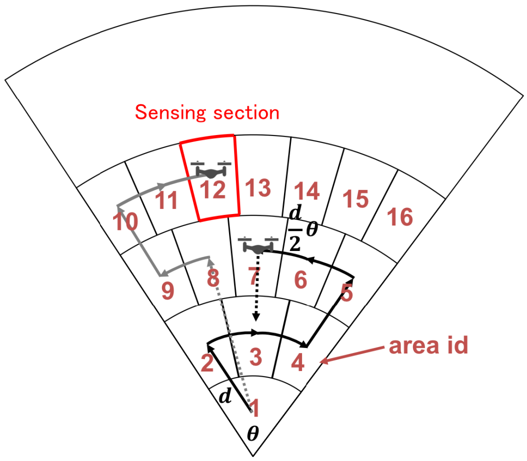

FIGURE 4. Sensing region of two-dimensional model.

neighboring section for the circumference is $\frac{1}{2}d\theta$. Therefore, when $\theta = 2$ (rad), all the distances between neighboring sections equal d, as shown in Figure 2. Therefore, the two-dimensional model in Figure 2 can be used in the same manner as a one-dimensional model, making the proposed scheduling method applicable here as well.

B. EVALUATION METRICS

We use the following three evaluation metrics from a user-centric viewpoint.

1) TWO TYPES OF ELAPSED TIMES

The first metric is divided into two types. The first type is 'elapsed time from start time' for each image (ETS), which is the elapsed time since the first UAV starts flying until each image result is obtained by the UD. This metric is important for a rescue team because they need to know about each sensing section as soon as possible to determine whether there are missing people. The second one is 'elapsed time after image acquisition' for each image (ETA), which is the elapsed time since an image is acquired at the corresponding sensing section until the image result is obtained by the UD. This metric is also valuable for a rescue team because it indicates the freshness of the information about each sensing section; the less the information is updated, the less reliable it is when searching for missing people.

2) NUMBER OF IMAGES SATISFYING TIME REQUIREMENTS

The second metric is number of images satisfying the time requirements: the number of images that satisfy a shorter ETA than a predetermined threshold at a certain time. This metric is important for a rescue team because they need to obtain fresh information while obtaining as many pieces of information as possible for a certain period.

3) INFORMATION VALUE OBTAINED BY USER

The third metric is the cumulative summation of how valuable the information obtained by the user each time is, i.e., information value. In a previous paper [29], the value function of the obtained image j at elapsed time from start time t was given as

$$V_j = 2^{-\frac{t}{T_{half}}}, \tag{9}$$

where T_{half} means the half-life of the value, which is a parameter set according to the time requirements in a disaster situation. The user obtains V_j when obtaining the result from processed image j. This metric allows us to measure how much valuable information the user obtains before the rescue team starts their rescue.

C. RESULTS

Figure 5 (a) plots the ETS against each area id. As shown in Fig. 5 (a), as the area id increases, the ETS monotonically increases in both methods. With the fixed method, as the area id increases, N^i giving the shortest ETS becomes larger for each area id. The performance of the proposed method is between that of the fixed method with $N^i = 10$ and $N^i = 40$. On the other hand, Figure 5 (b) plots the ETA against each area id. The ETA decreases in a regular manner with both methods. However, with the fixed method, as N^i is set smaller, the ETA becomes shorter. The performance of the proposed method is between that of the fixed method with

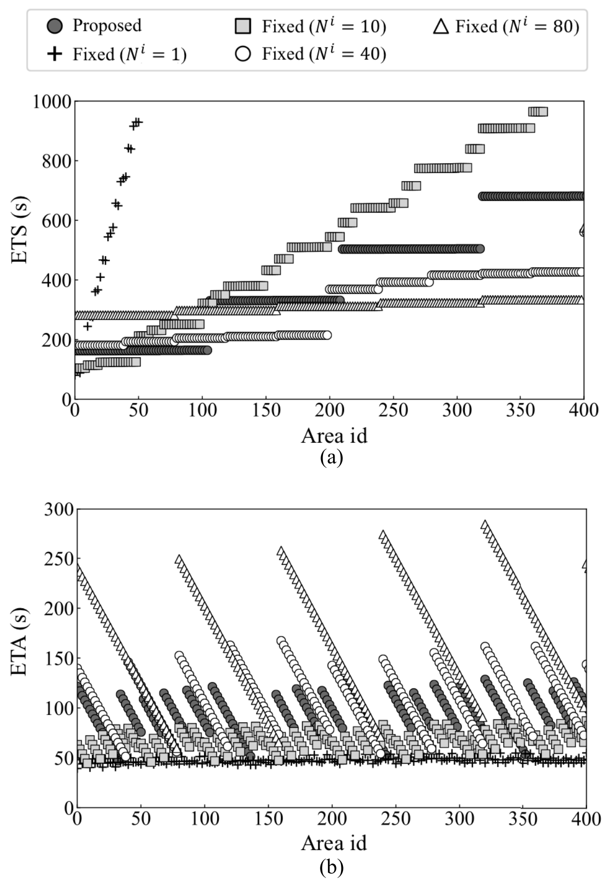

FIGURE 5. Two types of elapsed times. (a) Area id vs. ETS. (b) Area id vs. ETA.

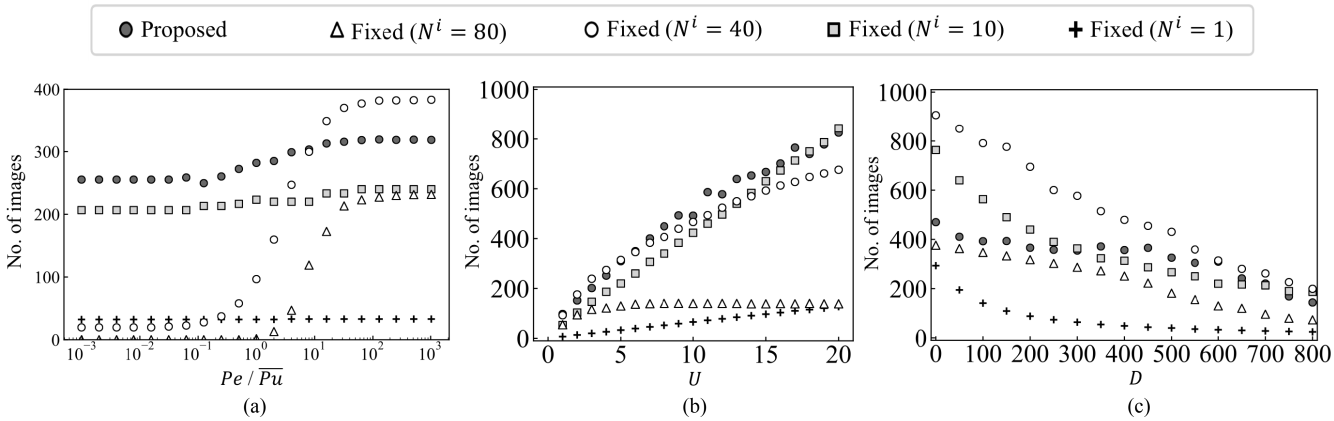

FIGURE 6. No. of images that had shorter ETA than 120 s at 600 s after start time. (a) Processing speed of ES vs. no. of images. (b) No. of UAVs vs. no. of images. (c) Distance between initial position and center of sensing block where area id is 1 vs. no. of images.

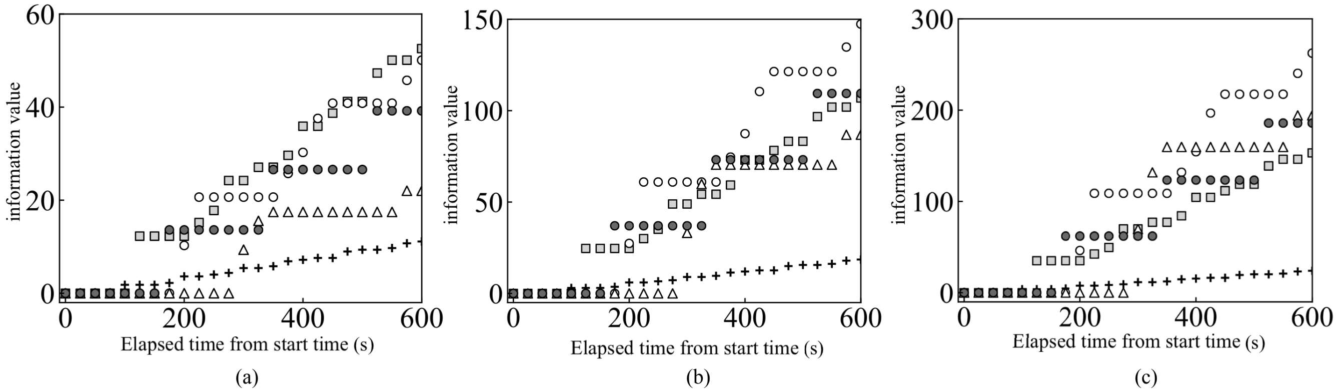

FIGURE 7. Information value. (a) Elapsed time from start time vs. information value (T_{half} = 30 s). (a) Elapsed time from start time vs. information value (T_{half} = 60 s). (a) Elapsed time from start time vs. information value (T_{half} = 120 s).

$N^i = 10$ and $N^i = 40$. With the fixed method, $N^i = 10$ and $N^i = 40$ are reasonable choices; the elapsed times are between the best and the third best, while their ETAs are much shorter than that of $N^i = 80$. The performance of the proposed method is between that of the fixed method with $N^i = 10$ and $N^i = 40$ in both types of elapsed times, enabling us to automatically achieve a reasonable N^i.

Figures 6 (a), 6 (b), and 6 (c) plot the numbers of images that satisfied shorter ETA than 120 secs at 600 secs against the processing speed at the ES regarding the number of images per unit time, number of UAVs, and distance from the initial position to the closest sensing block (area id = 1), respectively. The plots were obtained by averaging the results obtained from three trials. As shown on the left side of Figure 6 (a), the processing speed at the ES is sufficiently lower than the average processing speed at the UAVs, which corresponds to the case in which processing is performed mainly at UAVs not the ES. As shown on the right side of Figure 6 (a), the average processing speed at the UAVs is sufficiently lower than the processing speed at the ES, which corresponds to the case in which processing is performed mainly at the ES not at the UAVs. As shown in Figures 6 (a) and (b), the proposed method performs at a sufficient level for different values of $\frac{P_e}{P_u}$ and U, while different N^i was the best for different parameters with the fixed method. As shown in Figure 6 (c), the proposed method continues working at a sufficient level for different D, while the number of images with the fixed method monotonically decreases as D is set larger.

Figure 7 plots the information value against the elapsed time from start time. The half-life in Figures 7(a), 7(b), and 7(c) was 30, 60, and 120 secs, respectively. As shown in these figures, the information value monotonically increases with both methods. The proposed method performs at a sufficient level for a wide variety of half-lives, while different N^i is the best for different half-lives with the fixed method.

From the results in Figures 6 and 7, since the proposed method performs at a sufficient level without setting a reasonable N^i according to the parameter, unlike the fixed method, we can conclude that the proposed method performs best in this evaluation scenario.

VI. CONCLUSION

We proposed a scheduling method of multi-UAV search systems that, from a user-centric viewpoint, takes into account

$$\frac{N^i}{R^2(N^i)^2 + (4F + t^i_{\text{start}} - t^{i-1}_{\text{fin}})RN^i + 2F(2F + t^i_{\text{start}} - t^{i-1}_{\text{fin}})}\left(R = T_g + \frac{d}{v^i} + \frac{\mu_{d,e}P_e + \mu_{u,d}P_e + \mu_{u,d}\mu_{d,e}}{\mu_{u,d}\mu_{d,e}P_e + P^i_u(\mu_{d,e}P_e + \mu_{u,d}P_e + \mu_{u,d}\mu_{d,e})}\right) \tag{13}$$

the processing time of the acquired data and data-transfer time in areas where humans and ground vehicles cannot enter such as areas damaged by disaster. We first discussed a multi-UAV search system, which consists of a user device, multiple UAVs, and an edge server, and explained the system's flow. We then presented a utility-based problem formulation that ensures continuously updating information while obtaining as many pieces of information as possible for a certain period. We presented the results of a basic performance evaluation to verify that in terms of cumulative sum of utilities, the proposed method performed better than the fixed method, which simply uniformly assigns a fixed number of sensing sections to each UAV. In addition, a simulation using three evaluation metrics showed that the proposed method performs at a sufficient level from a user-centric viewpoint. Future work includes practical implementation.

APPENDIX
SOLUTION OF THE PROBLEM FORMULATION

It takes long time to solve (4) and (5) due to their computational complexities, and the calculation time for task allocation/scheduling may incur non-negligible overhead in the system; UAVs have to wait to start flying until task allocation and scheduling have been done for them. Therefore, to simplify the calculations of (4) and (5), it is first assumed with our scheduling method that all waiting times for UAV i are equal to zero and an approximate solution, N^i_{th}, is obtained. Then, by searching locally around N^i_{th}, our scheduling method takes into account all waiting times in (4) and (5) and finds the local optimal solution N^i_l. The following section explains the process of determining N^i_{th}. First, we set all the waiting times to zero. Then, we replace the second and fourth terms in (6) with $2F$ and M, respectively. Then, by substituting t^i_{fin} in (6) with (1), we obtain $\frac{\eta^i}{\Delta t^i}$ as below:

$$\frac{\eta^i}{\Delta t^i} = \frac{N^i}{N^i(T_g + \frac{d}{v^i}) + 2F + M} \times \frac{1}{N^i(T_g + \frac{d}{v^i}) + 2F + M + t^i_{\text{start}} - t^{i-1}_{\text{fin}}} \tag{10}$$

where, by regarding N^i as a constant, only M is a variable and $\frac{\eta^i}{\Delta t^i}$ varies depending on N^i_u and N^i_e. Since $\frac{\eta^i}{\Delta t^i}$ is always positive, M takes the minimum value when $\frac{\eta^i}{\Delta t^i}$ takes the maximum value. Although N^i, N^i_u, and N^i_e are integers, we consider them as real numbers. Considering $N^i = N^i_u + N^i_e$, on the assumption that $\frac{N^i_u}{P^i_u}$ equals $\frac{N^i_e}{\mu_{u,d}} + \frac{N^i_e}{\mu_{d,e}} + \frac{N^i_e}{P_e}$, we can obtain N^i_u and N^i_e that satisfy $0 \le N^i_u$ and $N^i_e \le N^i$ as follows:

$$N^i_u = \frac{P^i_u(\mu_{d,e}P_e + \mu_{u,d}P_e + \mu_{u,d}\mu_{d,e})}{\mu_{u,d}\mu_{d,e}P_e + P^i_u(\mu_{d,e}P_e + \mu_{u,d}P_e + \mu_{u,d}\mu_{d,e})}N^i \tag{11}$$

$$N^i_e = \frac{\mu_{u,d}\mu_{d,e}P_e}{\mu_{u,d}\mu_{d,e}P_e + P^i_u(\mu_{d,e}P_e + \mu_{u,d}P_e + \mu_{u,d}\mu_{d,e})}N^i \tag{12}$$

When M takes the minimum value, $\frac{N^i_u}{P^i_u}$ is theoretically equal to $\frac{N^i_e}{\mu_{u,d}} + \frac{N^i_e}{\mu_{d,e}} + \frac{N^i_e}{P_e}$, while N^i_u and N^i_e become (11) and (12), respectively. As N^i becomes larger, $\frac{N^i_u}{P^i_u}$ becomes closer to $\frac{N^i_e}{\mu_{u,d}} + \frac{N^i_e}{\mu_{d,e}} + \frac{N^i_e}{P_e}$. Thus, $\frac{N^i_u}{P^i_u} = \frac{N^i_e}{\mu_{u,d}} + \frac{N^i_e}{\mu_{d,e}} + \frac{N^i_e}{P_e}$ is established. As a result, $\frac{\eta^i}{\Delta t^i}$ in (10) is given as

By differentiating with respect to N^i, we obtain:

$$\frac{-R^2(N^i)^2 + 2F(2F + t^i_{\text{start}} - t^{i-1}_{\text{fin}})}{\{R^2(N^i)^2 + (4F + t^i_{\text{start}} - t^{i-1}_{\text{fin}})RN^i + 2F(2F + t^i_{\text{start}} - t^{i-1}_{\text{fin}})\}^2} \tag{14}$$

When $t^i_{\text{start}} \le t^{i-1}_{\text{fin}} - 2F$, (13), as shown at the top of this page, decreases monotonically as N^i increases and takes the maximum value when N^i_{th} is N^i_{MIN}. When $t^i_{\text{start}} > t^{i-1}_{\text{fin}} - 2F$, $\frac{\eta^i}{\Delta t^i}$ is a convex function taking the maximum when N^i is $\frac{\sqrt{2F(2F + t^i_{\text{start}} - t^{i-1}_{\text{fin}})}}{R}$. Note that N^i is chosen so that the denominator of (13) does not become zero. Through the above procedure, we can obtain N^i_{th} as follows:

$$N^i_{th} = \begin{cases} \dfrac{\sqrt{2F(2F + t^i_{\text{start}} - t^{i-1}_{\text{fin}})}}{R}, \\ \qquad \left(N^i_{\text{MIN}} \le \dfrac{\sqrt{2F(2F + t^i_{\text{start}} - t^{i-1}_{\text{fin}})}}{R}\right) \\ N^i_{\text{MIN}}, \quad \left(\dfrac{\sqrt{2F(2F + t^i_{\text{start}} - t^{i-1}_{\text{fin}})}}{R} < N^i_{\text{MIN}}\right) \end{cases} \tag{15}$$

In determining the local optimal solution N^i_l, the range of local searching with the proposed scheduling method was set wide enough to ensure that N^i_l equals the true optimal solution. We also assumed that the time required for determining N^i_l is negligible since the complexity of the scheduling algorithm is quite simple, the calculation can finish in the previous round before the UAV starts flying.

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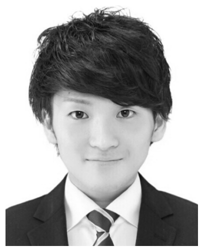

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