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Multi-UAV Allocation Framework for Predictive Crime Deterrence and Data Acquisition

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A B S T R A C T

The recent decline in the number of police and security force personnel has raised a serious security issue that could lead to reduced public safety and delayed response to crimes in urban areas. This may be alleviated in part by utilizing micro or small unmanned aerial vehicles (UAVs) and their high-mobility on-board sensors in conjunction with machine-learning techniques such as neural networks to offer better performance in predicting times and places that are high-risk and deterring crimes. The key to the success of such operation lies in the suitable placement of UAVs. This paper proposes a multi-UAV allocation framework for predictive crime deterrence and data acquisition that consists of the overarching methodology, a problem formulation, and an allocation method that work with a prediction model using a machine learning approach. In contrast to previous studies, our framework provides the most effective arrangement of UAVs for maximizing the chance to apprehend offenders whilst also acquiring data that will help improve the performance of subsequent crime prediction. This paper presents the system architecture assumed in this study, followed by a detailed description of the methodology, the formulation of the problem, and the UAV allocation method of the proposed framework. Our framework is tested using a real-world crime dataset to evaluate its performance with respect to the expected number of crimes deterred by the UAV patrol. Furthermore, to address the engineering practice of the proposed framework, we discuss the feasibility of the simulated deployment scenario in terms of energy consumption and the relationship between data analysis and crime prediction.

1. introduction

The shortage of police and security personnel is a serious problem around the world, as it leads to a lack of guardians and slower response times. In England and Wales, the number of police officers was roughly 120,000 in 2016, which is approximately 14% lower than in 2009 [1].

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To alleviate this situation, technology related to micro or small unmanned aerial vehicles (UAVs) and prediction technology utilizing machine learning have shown promise. Since UAVs have high mobility and can be equipped with visual sensors, they can be used to cover areas that are short of personnel over a wide region [2–7]. Indeed, several studies have proposed the use of UAV policing systems as a viable solution in the fight against crime [8–10]. It was reported that such UAV policing systems work well for extensive crime deterrence, as they are not limited to crimes that occur outside of buildings [11]. Another report has suggested a solution for crime deterrence that works for all categories of crimes, though the solution did not use UAVs [12]. In general, when (human) police officers are patrolling outside near a building, crimes are less likely to occur both inside and outside of the building because criminals do not think they will be able to escape easily. We presume this hypothesis is applicable for UAV policing systems, which was demonstrated by the above Mexico police example [11].

In a similar vein, the development of machine learning technology enables crime to be predicted from a variety of crime-related data [13–15]. In the United States, several states (including California, Washington, South Carolina, Arizona, Tennessee, and Illinois) have adopted predictive policing programs [16]. In Japan, the Kanagawa Prefectural Police have started a trial deployment of predictive policing in anticipation of the Tokyo Olympics originally scheduled for 2020. Currently, several law enforcement agencies (Chicago Police, NYPD, and Boston Police) offer their crime-related data to the public via open data platforms such as Kaggle and the IBM Open Crime Data API [17,18]. By using crime prediction results, personnel can be deployed in areas where crime is likely to occur in advance.

A research question in this paper is how UAVs instead of personal can be deployed effectively if crime prediction results are available. Running a crime prediction test in advance would allow us to deploy UAVs strategically in areas where crime is more likely to occur. The aim of this work is to study how to allocate UAVs in such a way that data is acquired and utilized for improving the next cycle of crime prediction while covering areas where crimes are currently likely to occur. No previous work has done this before, and it could potentially become a promising solution for crime deterrence in the future.

This paper proposes a multi-UAV allocation framework for predictive crime deterrence and data acquisition that consists of the overarching methodology, a problem formulation, and an allocation method that work with a prediction model using a machine learning approach. Priority for the UAV deployment will be given to areas that maximize the chance of crime deterrence, as this will increase the probability of helping to apprehend offenders whilst also acquiring data that will help improve the performance of subsequent crime prediction. This paper presents the system architecture assumed in this study, followed by a detailed description of the methodology, the formulation of the problem, and the UAV allocation method of the proposed framework. It then presents a simulation study that assumes a scenario where the police force aims to deter crime by using our framework. Our objective at this stage of the study is to evaluate the effectiveness of our framework by cross-examining its performance with a real-world crime dataset. Furthermore, to address the engineering practice of the proposed framework, we discuss the feasibility of the simulation scenario in terms of energy consumption and the relationship between data analysis and crime prediction.

The contributions of this paper are summarized as follows: 1) this paper proposes a multi-UAV allocation framework for predictive crime deterrence and data acquisition; 2) the proposed framework consists of the overarching methodology, a problem formulation, and an allocation method that work with a prediction model using a machine learning approach; 3) the proposed framework provides the most effective arrangement of UAVs for maximizing the chance to apprehend offenders whilst also acquiring data that will help improve the performance of subsequent crime prediction; 4) this paper presents the system architecture assumed in this study, followed by a detailed description of the methodology, the formulation of the problem, and the UAV allocation method of the proposed framework; 5) the proposed framework is tested using a real-world crime dataset to evaluate its performance with respect to the expected number of crimes deterred by the UAV patrol; 6) to address the engineering practice of the proposed framework, this paper discusses the feasibility of the simulated deployment scenario in terms of energy consumption and the relationship between data analysis and crime prediction. These contributions will lead to the establishment of an ecosystem for public services including policing by leveraging the Internet-of-Things (IoT) technologies such as autonomous UAVs.

The remainder of this paper is organized as below. In Section 2 of this paper, we discuss related work, including studies on flight autonomy, which is a technical requirement in our work. In Section 3, we present the system architecture assumed in this study and discuss the details of the proposed framework. Section 4 provides the results of performance evaluations with a real-world crime dataset and discusses the feasibility of the simulation scenario we assume. Finally, conclusions and future work are given in Section 5.

2. Related work

2.1. Crime data analysis

Research efforts on crime data analysis are rife, with many studies aimed at helping law enforcement agencies to better understand the patterns of crime and to use that knowledge for reducing crime [19–21]. Increasing volumes and types of crime data are being released to the public, against which a number of different analytical methods have been presented.

For example, spatiotemporal methods are effective for interpreting spatially and temporally tagged crime data. Duan et al. divided the urban area of New York City into disjoint regions and counted the number of crimes that occurred in each region every day [22]. They then applied deep convolutional neural networks (CNNs) to the data to predict the crime risk

Table 1
Comparison with other existing works. -, +, and ++ indicate 'not considered,' 'considered,' and 'well considered,' respectively. ML stands for machine learning.

Item	Kim 2018 [2]	Giyenko 2016 [3]	Ermacora 2014 [8]	Merwaday 2015 [9]	Karim 2017 [37]	Our work
UAV allocation	+	+	-	++	-	++
Prediction using ML	-	-	-	-	-	++
Data importance extraction	-	-	-	-	-	++
Real dataset	-	-	-	-	++	++
Simulation	-	-	-	+	-	++
Experiment	-	-	+	-	+	-
Energy analysis	+	-	-	-	-	++

in each region on the following day. Wang et al. also applied CNNs to a spatiotemporal distribution of crimes to predict future crime distribution in the Los Angeles area [13]. Shiode and Shiode developed a micro-scale geo-surveillance method to accurately detect emerging clusters of a spatiotemporally significant concentration of crimes to improve the effectiveness of hotspot policing [23,24].

Computer vision (CV)-based methods are being developed for interpreting mobile and still images. Arietta et al. used a set of street-level images to first identify the visual elements in the images (e.g., fire escapes, high-density apartment windows, and broken store signs) and then predict the occurrence rate of various events such as violent crimes [25]. Beiji et al. applied semantic concept detection to video data for detecting and monitoring crime hotspots [26].

Multi-modal methods use a combination of crime data. Bogomolov et al. used human behavioral data derived from anonymized and aggregated mobile network activity and combined them with demographic data to predict crime hotspots in London [27]. Gerber et al. performed Twitter-specific linguistic analysis and statistical topic modeling on spatiotemporally tagged tweet data to predict the occurrence of crime [28]. Kang et al. presented a deep neural network (DNN)-based method and applied it to a series of online databases of crime statistics, demographic and meteorological data, and streetscapes in Chicago to predict crime occurrence [14].

Other methods including text and natural language processing (NLP) [29,30], crime patterns and evidence-based methods [31–35], and prisoner-based methods [36] have also been considered.

Although these methods use various types of data, they do not consider how to collect such data using UAVs. Also, their main interest is typically the accuracy of results obtained from data analysis. This paper focuses on the allocation of UAVs for sensor data collection, while the performance of data analysis is outside its scope.

2.2. UAV applications for crime prevention

On the operational side of a UAV system, use of a mobile platform such as UAVs for surveillance is expected to increase security and reduce crime rates [2,3]. Ermacora et al. studied a high-level cloud platform that manages a number of UAVs to prevent crimes [8]. Merwaday et al. explored a new generation of broadband public safety communication (PSC) systems that use UAVs for public safety by preventing acts of crime and terrorism [9]. Karim et al. proposed a drone plane for monitoring and targeting street criminals [37] that uses real-time image processing techniques such as object detection and classification.

Table 1 summarizes the comparison of our work with the existing works mentioned above. Merwaday and Güvenc considered the optimization of multi-UAV allocation, though their objective was to maximize throughput of a UAV-aided wireless network in the disaster-damaged situation [9]. Karim et al. used a real dataset of images in which a person is shooting or holding a gun to evaluate image classification for street crime detection [37]. Our work presents the problem formulation of multi-UAV allocation, prediction using machine learning, data importance extraction, simulation using a real dataset, and discussion of energy analysis, which clearly distinguishes it from the other existing works. Particularly, the proposed framework is ground-breaking because the existing works did not consider predictive policing using machine learning.

2.3. Flight autonomy

Flight autonomy is another technical requirement in our work. Kan et al. demonstrated autonomous flight of an UAV by using the global positioning system (GPS) [38]. Dinesh et al. also presented autonomous flight of a UAV using GPS. They highlighted surveillance for counter terrorism as a specific application [39]. Although both studies reported that their experiments were generally successful, these experiments were not large-scale in scope. On the industrial side, Workhorse Group developed delivery UAVs that autonomously fly from conventional delivery vehicles to destinations [40]. The autonomous flight technology of UAVs most recently developed by Bell Textron Inc. has enabled UAVs to fly 35 mi in 30 min for a flight mission [41]. These initiatives suggest that the flight autonomy of UAVs is already being commercialized and that the idea of autonomous flight will soon have even wider exposure in the industry.

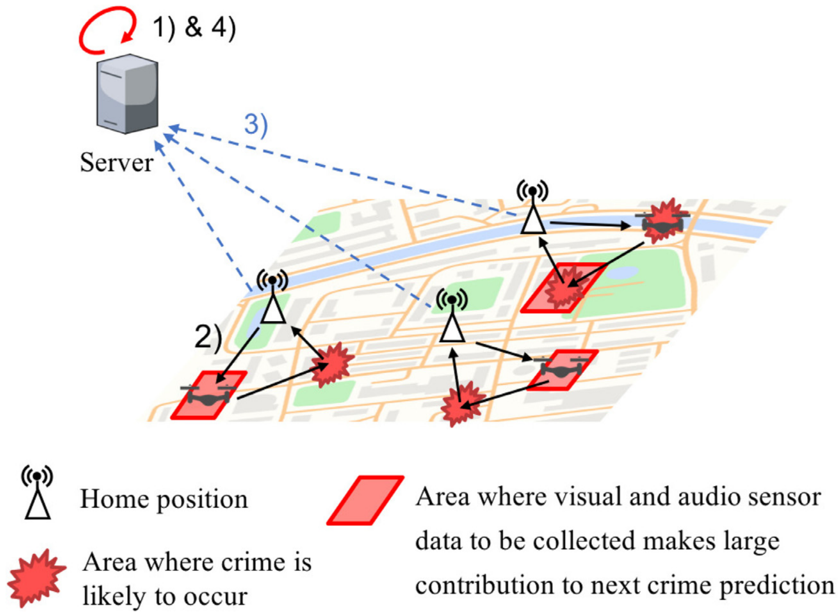


Fig. 1. System architecture assumed in this study. Server performs 1) UAV allocation and 4) crime prediction. UAVs are used to 2) patrol areas and 3) collect visual and audio sensor data.

3. Proposed framework

3.1. System architecture

Figure 1 shows the system architecture assumed in this study. It consists of a server, home positions, and UAVs with onboard visual and audio sensors. The server is the central operating entity in the system; it aggregates data acquired by UAVs, performs crime prediction, and allocates UAVs to patrol areas. The home positions are the initial positions of UAVs and work as their battery exchange points and the access point for communication between the server and UAVs. Each UAV is operated by a server, patrols the areas assigned to it, and returns to the home position for battery exchange and communication.

Note that we do not assume UAVs need to detect crimes by themselves. The video processing consumes a lot of energy, and the onboard power of a UAV is typically insufficient to support such data processing. In addition, readers may think that UAVs should transmit collected data not only at the home position but also via long-range wireless networks on a real-time and online basis to prevent crimes before they are committed. However, as shown in Fig. 4 in Section 4, the control cycle of the proposed framework can be six hours or longer to obtain the data correlation required for crime prediction. Therefore, it is reasonable to assume that UAVs go back to their home positions to upload their data to the server.

The flow of the system comprises four steps: 1) UAV allocation, 2) patrol, 3) collection of visual and audio sensor data, and 4) crime prediction.

3.1.1. UAV allocation

To maximize the possibility that UAVs cover areas where crimes actually occur, the server allocates UAVs beforehand so that each one patrols blocks of high importance. Here, a block means the unit size of the area a UAV covers.

3.1.2. Patrol

Each UAV starts flying from the home position in accordance to the flight instructions from the server, patrols blocks on the basis of the allocation in step 1), and acquires audio and visual sensor data with onboard sensors. After a certain period of time, the UAV returns to the home position.

3.1.3. Collection of visual and audio sensor data

The server aggregates the visual and audio sensor data from UAVs for analysis as well as archiving. The data is sent via the home position.

3.1.4. Crime prediction

The server runs a forecast model using a machine learning technique to predict when and where crimes are likely to occur. The input data for the prediction model is information extracted from the audio and visual sensor data collected by

UAVs, and the output data is the expected number of a specific type of crime incident in each block within a certain period of time.

The breakdown of the input data can be darkness, quietness, and the number of people in the area. In general, it is reported that areas with poor lighting, little activity, and few pedestrians are considered to have a higher risk of crime. We can expect that the visual and audio sensor data acquired by UAVs will contain those kinds of information useful for crime prediction. Note that this approach is one of the multi-modal methods introduced in Section 2.

3.2. Methodology

The first technical challenge in this research is that there may be tradeoffs in the allocation of UAVs between areas suitable for deterring crimes and those for acquiring data for crime prediction. If we focused solely on increasing the possibility that UAVs cover areas where crimes occur, from the myopic view, we would just allocate UAVs to areas where crimes are likely to occur, which may result in missed data that should be acquired for improving the accuracy of the next crime prediction. Therefore, the proposed framework considers both of these aspects, as described in detail in Section 3.3.

The second technical challenge is that we need to know beforehand in which areas UAVs can acquire data that will help improve the accuracy of the next crime prediction. This is obviously difficult because the accuracy of a prediction only becomes clear after crimes have actually transpired. We need an effective means to estimate the 'importance' of each data on crime prediction before the actual deployment. We introduce feature selection as a possible solution for this. It enables us to extract important data from the prediction model of machine learning and helps reduce redundancy of data for efficient computing. We apply this to our framework for assessing the importance of data and then determine the UAV allocation in accordance with the obtained importance score.

Our framework introduces two metrics as the importance of each block. The first metric is how many crimes are covered by UAVs using the results of crime prediction, referred to as a "deterrent metric." It is important to patrol blocks where the deterrent metric is large in order to allocate UAVs to areas where crimes are likely to occur. The second metric is how much the collected visual and audio sensor data contributes to improving the accuracy of the next prediction, referred to as an "acquisition metric." To maintain high prediction accuracy continuously for a long period, not only blocks where the deterrent metric is large but also those where the acquisition metric is large must be covered to maximize the possibility that UAVs cover areas where crimes actually occur.

3.3. Problem formulation

This section discusses the problem formulation of allocating all UAVs (mentioned in Section 3.1.1). First, we define the control cycle of the system. It is assumed that a set of UAVs is allocated to blocks every control cycle and only one at most UAV is allocated to a block during a control cycle. It is also assumed that crimes at the next control cycle are predicted and the prediction is performed every control cycle. We consider the current control cycle i for the problem formulation.

We here explain given parameters in the problem formulation. Let L denote a set of blocks. V denotes the number of available UAVs. N_l^i denotes the number of crimes that will occur in block $l \in L$ at the current control cycle i, which is predicted at the previous control cycle $i-1$. The data acquired at i is used for prediction from subsequent control cycles $m = i+1$ to $m = i+p$, where p is the number of control cycles dealt with as the input data length in machine learning. w is a weight that ranges from 0 to 1.

Next, we explain decision variables in the problem formulation. r_l^i is a binary decision variable that is set to 1 if a UAV is allocated to block $l \in L$, and 0 otherwise. R^i denotes a set of decision variables $r_l^i, l \in L$, i.e., $R^i = \{r_l^i | l \in L\}$. We denote the probability that $r_l^m = 1$ and the number of predicted crimes in block $l \in L$ at subsequent control cycles $m = i+1$ to $m = i+p$ as $P_l^m(R^i)$ and $N_l^m(R^i)$, respectively. Since r_l^i in block $l \in L$ affects prediction results at subsequent control cycles $m = i+1$ to $m = i+p$, $P_l^m(R^i)$ and $N_l^m(R^i)$ are decision variables dependent on r_l^i in block $l \in L$.

The notations used in the problem formulation are summarized in Table 2.

The objective of the problem formulation in our framework is to maximize the number of crimes covered by UAVs at not only control cycle i but also control cycles $m = i+1$ to $m = i+p$. It is enabled by considering data acquisition at control cycle i for crime prediction at subsequent control cycles $m = i+1$ to $m = i+p$.

The problem formulation is described below by using the above notations:

$$\max_{R^i} \quad w \sum_{l \in L} r_l^i N_l^i + (1-w) \sum_{m=i+1}^{i+p} \sum_{l \in L} P_l^m(R^i) N_l^m(R^i) \tag{1}$$

$$\text{s.t.} \quad \sum_{l \in L} r_l^i \le V. \tag{2}$$

The first term of (1) represents the sum of the number of crimes covered by all UAVs at control cycle i and corresponds to the deterrent metric in Section 3.1.1. The second term represents the sum of the number of crimes covered by all UAVs from control cycles $m = i+1$ to $m = i+p$ and corresponds to the acquisition metric in Section 3.1.1. When $w = 1$, (1) considers only the first term (deterrent metric), which means that UAVs are allocated to maximize the expected number of crimes

Table 2
Notations used in problem formulation.

Given parameters	
i	Current control cycle.
L	Set of blocks.
V	Number of available UAVs.
N_l^i	Number of predicted crimes in block $l \in L$ at control cycle i
p	Number of control cycles as input data length in machine learning.
w	Weight between 0 and 1 for deterrent and acquisition.
Decision variables	
r_l^i	Binary variable. It is set to 1 if UAV is allocated to block $l \in L$ at i, and 0 otherwise.
R^i	Set of $r_l^i, l \in L$, i.e., $R^i = \{r_l^i \mid l \in L\}$.
$N_l^m(R^i)$	Number of predicted crimes in block l at subsequent control cycle m, which is a function of R^i.
$P_l^m(R^i)$	Probability that $r_l^m = 1$ in block l at subsequent control cycle m, which is a function of R^i.

they cover at the current control cycle. When $w = 0$, (1) considers only the second term (acquisition metric), which means that UAVs are allocated to acquire the most useful data for the prediction of crimes that will occur at the subsequent control cycles. Equation (2) indicates that the number of blocks to which UAVs are allocated does not exceed V. R^i is determined such that the value weighting the two terms with w and $1 - w$ is maximized subject to the constraint in (2).

3.4. Allocation using feature selection

N_l^i in the first term of (1) should contain some error because, in general, prediction is not always perfect. To consider this inaccuracy, we here redefine N_l^i as $\alpha_l^i \hat{N}_l^i$, in which $\hat{N}_l^i$ is the number of crimes predicted by the system in block l at control cycle i. α_l^i is the weight between 0 and 1 depending on the prediction accuracy and is given as

$$\alpha_l^i = \frac{1}{K} \sum_{k=1}^{K} (1 - D_l^{i-k}), \tag{3}$$

where K denotes the number of past control cycles to consider. Equation (3) is the sliding window time average of $(1 - D_l^{i-k})$ over control cycles $i - K$ to $i - 1$ [42]. D_l^j is defined as

$$D_l^j = \begin{cases} \dfrac{\left|A_l^j - N_l^j\right|}{\frac{1}{|L|} \sum_{l \in L} A_l^j} \left(\left|A_l^j - N_l^j\right| < \frac{1}{|L|} \sum_{l \in L} A_l^j \right) \\ 1 \left(\left|A_l^j - N_l^j\right| \geq \frac{1}{|L|} \sum_{l \in L} A_l^j \right) \end{cases}, \tag{4}$$

where A_l^j denotes the number of crimes actually recorded at block l at control cycle j. $\left|A_l^j - N_l^j\right|$ represents the prediction error, while $\frac{1}{|L|} \sum_{l \in L} A_l^j$ represents the average number of crimes over all the blocks. D_l^j becomes 0 when there is no prediction error. As $\left|A_l^j - N_l^j\right|$ becomes larger, D_l^j becomes closer to 1, and when $\left|A_l^j - N_l^j\right| \geq \frac{1}{|L|} \sum_{l \in L} A_l^j$, D_l^j becomes 1. Equation (4) is inspired by the definition of relative error [43].

Regarding the second term of (1), $P_l^m(R^i)$ and $N_l^m(R^i)$ are hard to obtain at control cycle i; they will become available at subsequent control cycle m after R_i is determined. Therefore, in the proposed framework, the acquisition metric calculated from the feature selection method of machine learning [44–48] is used instead of the value of the second term of (1). From the above, the problem formulation of actual allocation is given as

$$\max_{R^i} \quad w \sum_{l \in L} r_l^i \alpha_l^i \hat{N}_l^i + (1 - w) \sum_{l \in L} r_l^i I_l^i. \tag{5}$$

The purpose of feature selection is to select a subset of input variables that efficiently and effectively represents the 'feature' of the prediction model. In other words, feature selection works to estimate the importance of the input variables used in the prediction by calculating the contribution of variables to the prediction. In the proposed framework, input variables in the prediction model are for each block and each control cycle. Therefore, feature selection enables us to estimate the expected improvement in prediction performance by data to be acquired by UAVs in each block and each control cycle. In

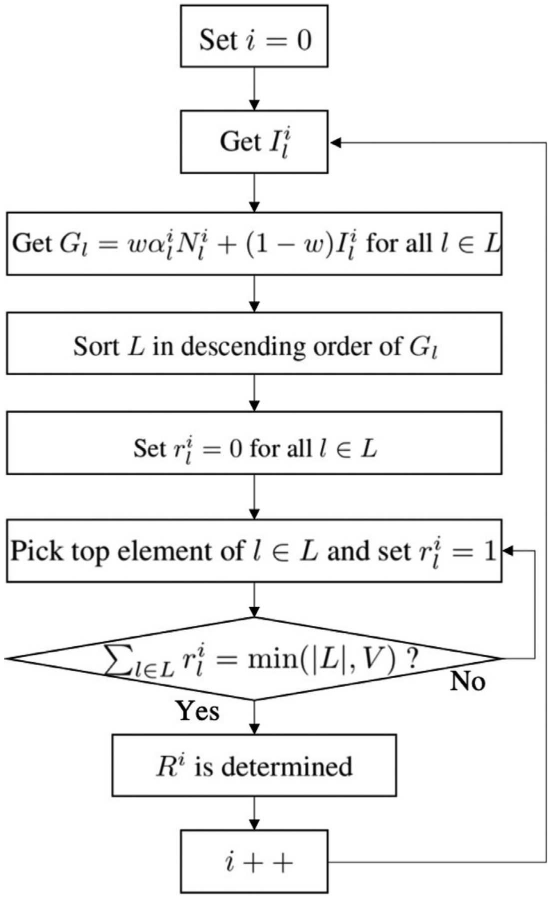


Fig. 2. Flowchart of UAV allocation in proposed framework.

the evaluation performed in this paper, as we will show in Section 4.2, we use long short-term memory (LSTM) as the machine learning for prediction and a perturbation method as the feature selection for importance estimation.

Here, let us consider how we solve (5). We first note that r_l^i commonly appears inside $\Sigma_{l \in L}$ in the first and second terms. Next, $w\alpha_l^i \hat{N}_l^i + (1-w)I_l^i$ for block l, which is defined here as the gain of block l, G_l, is independent of every other block. Therefore, determining R^i that maximizes (5) is equivalent to allocating UAVs from the top blocks with the largest G_l. This is enabled by using an efficient sorting algorithm such as quicksort [49], which is scalable against the increases of the number of blocks, $|L|$, and the number of UAVs. Thus, (5) enables us to solve the problem formulation in our framework given as (1), which is one of the main contributions in this study. Finally, Figure 2 shows the flowchart of UAV allocation in the proposed framework.

4. Evaluation

We consider a simulation to evaluate the effectiveness of the proposed framework. To make our simulation as realistic as possible, we used a real dataset of crimes, a real geographical map, and the specifications of a real commercialized UAV. To extensively and solidly evaluate performance, we use multiple datasets in Sections 4.3 and 4.4. In Section 4.5, we discuss the real-world feasibility of the simulation scenario particularly in terms of the costs associated with the energy consumption. Although a real experiment would seem more beneficial than a simulation, in reality, the strict regulations concerning UAV usage in residential and commercial areas make it impossible to obtain extensive and solid results from a large-scale experiment about multi-UAV allocation for predictive policing. Considering this fact, a simulation study is beneficial at this stage as a driving force for relaxing such regulations by showing the effectiveness of multi-UAV allocation for predictive policing.

The simulation evaluated the effectiveness of the proposed framework in terms of the expected number of crimes deterred by UAV patrolling. A scenario in which the police aim for crime deterrence using the proposed framework in Fig. 1 is assumed. UAVs acquire the visual and audio sensor data to be used for crime prediction in all blocks for a certain period. Then, on the basis of the acquired predictive data, the server creates the prediction model and predicts the number of

Table 3
Simulation parameters.

Parameter	Value
Number of blocks	271
Learning period	Jan. 2015–July 2016
Predicting period	Aug. 2016–Dec. 2016
Input data	Number of minor offences over latest ten control cycles
Output data	Number of major offences at next control cycle
Number of UAVs	150
Number of past control cycles considered in α_l^i (N)	3
Time length (Δt)	1, 6, 12, 24 hour(s)
Flying speed of UAVs (v)	15 m/s

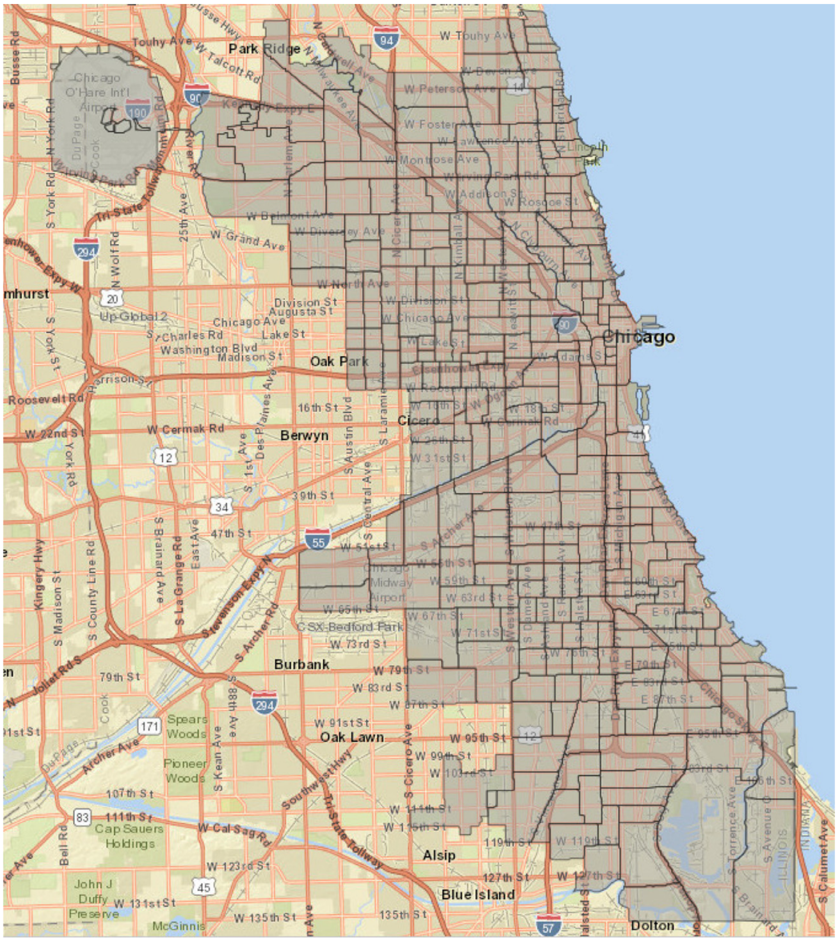


Fig. 3. All 271 blocks in the City of Chicago [50].

crime incidents in each block. According to the result of this crime prediction, UAVs acquire the data in the blocks assigned to them and the data is then used for the next prediction. The subsequent flow is as described in Section 3.1.

4.1. Simulation parameters

The parameters used in our simulation are listed in Table 3. The flight paths of UAVs for each control cycle are determined such that (5) is maximized. We denote the time interval of the control cycle as Δt. Equation (5) is solved by a sorting algorithm. For our simulation, we used an open crime dataset available via Kaggle [17], which is extracted from the Chicago Police Department's Citizen Law Enforcement Analysis and Reporting System. This dataset records the type, location, and time of each recorded crime that occurred in the City of Chicago from January 2001 to January 2017. As shown in Fig. 3, the City of Chicago consists of 271 blocks in total, which correspond to block l. Technically, the flight altitude and the field of view influence the size of the area covered by UAVs. Suppose that the direction of the sensor is vertical to the ground.

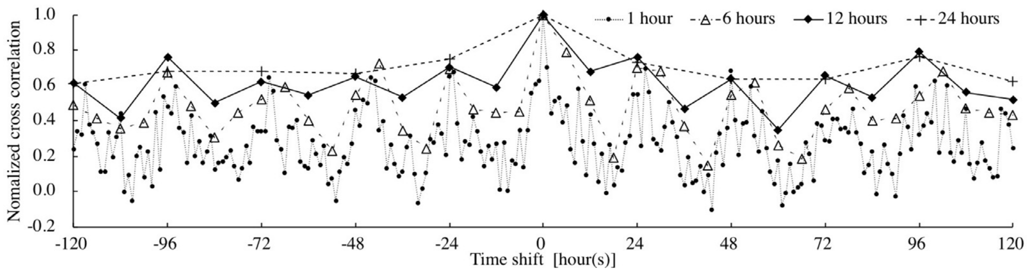


Fig. 4. Normalized cross correlation of numbers of major crimes with numbers of minor crimes in each block.

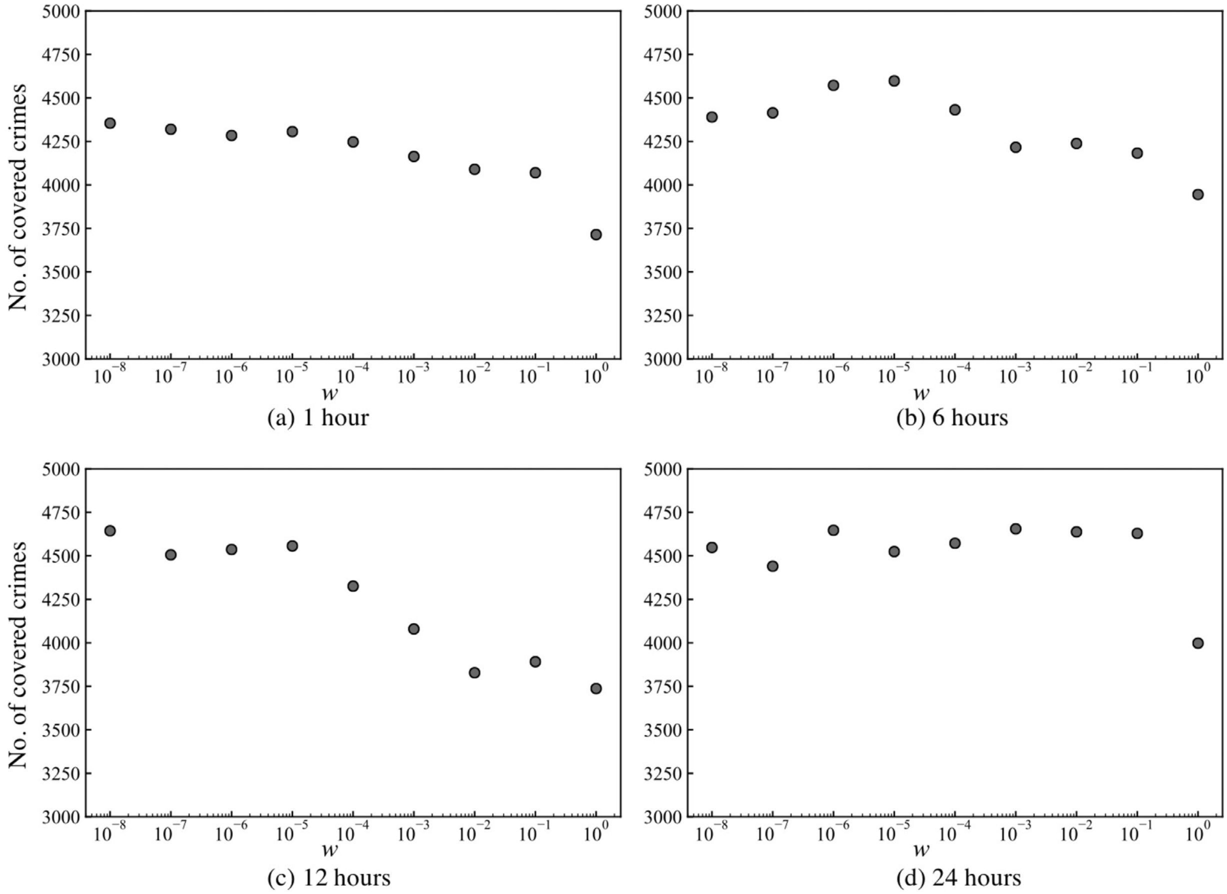


Fig. 5. Total number of crimes covered by UAVs vs. weight. Against 7,857 cases of all crimes recorded, the total numbers of predicted crimes across all areas were 118,294, 7,066, 6,050, and 6,630 when Δt = 1, 6, 12, and 24, respectively.

If the flight altitude and the field of view (angle) are h and θ, the width of the area is $h\tan\theta$. In our evaluation, the size of each block covered by UAVs is determined by the dataset, as illustrated in Fig. 3. Note that we assumed each UAV flies around within the block allocated to it at every time interval to ideally cover the entire range of the block. We used the criminal records from January 2015 to July 2016 to make the prediction model, while the criminal records from August 2016 to December 2016 were predicted.

We treated major offences of the dataset (burglary, sexual assault, homicide, and arson) as the output data in crime prediction and used minor offences (all others) as the input data. Although existing studies in criminology mainly point to the indicator theory whereby certain petty crimes tend to evolve into major offences, the overall relationship between minor and major offences has yet to be systematically studied. In this study, we assume there is a positive correlation between the two; i.e., places where a large volume of minor offence is observed are likely to also suffer from more frequent counts of major offences. We will demonstrate this by applying correlation analysis to empirical data. Figure 4 shows the result of the analysis. We dealt the list of the numbers of crimes in each block as vector data; the lists of the numbers of minor and

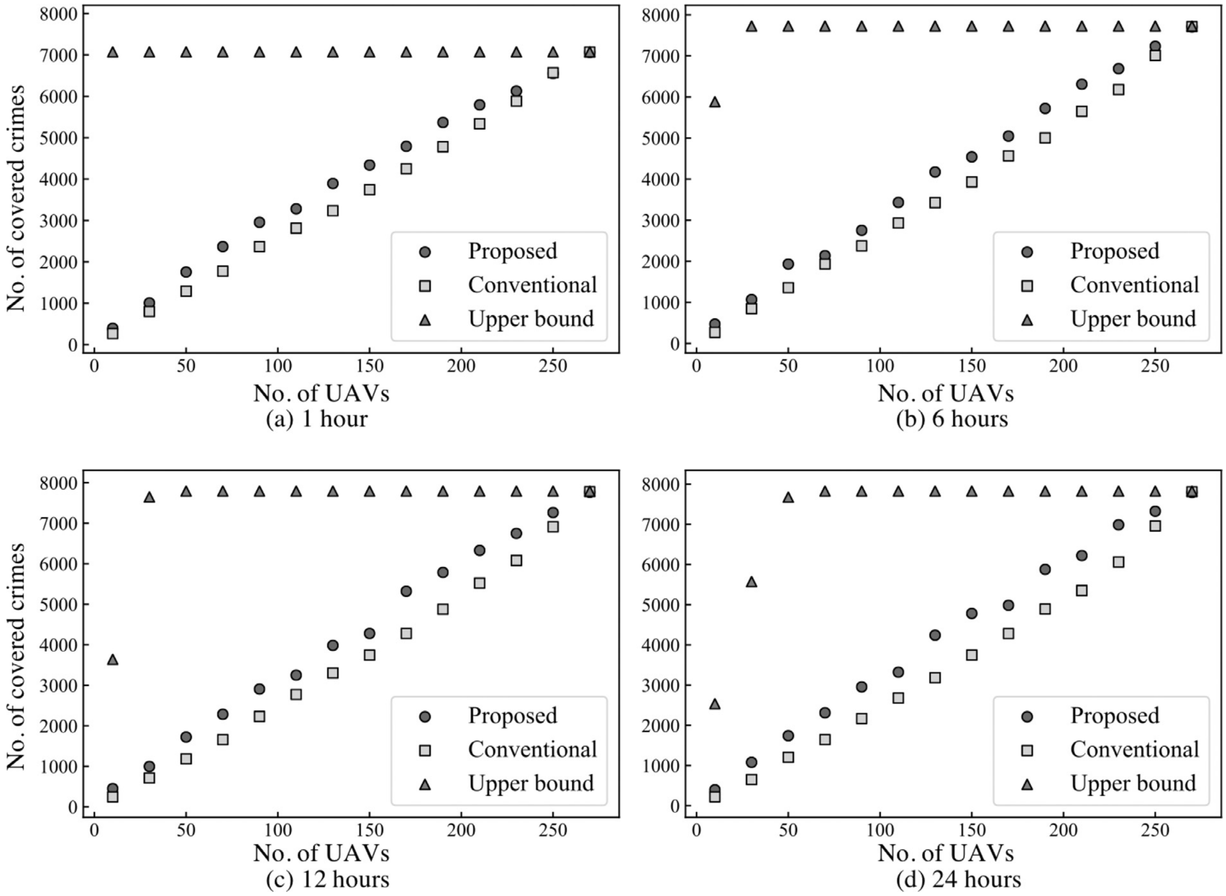


Fig. 6. Total number of crimes covered by UAVs vs. number of UAVs. Against 7,857 cases of all crimes recorded, the total numbers of predicted crimes across all areas were 118,294, 7,066, 6,050, and 6,630 when Δt = 1, 6, 12, and 24, respectively.

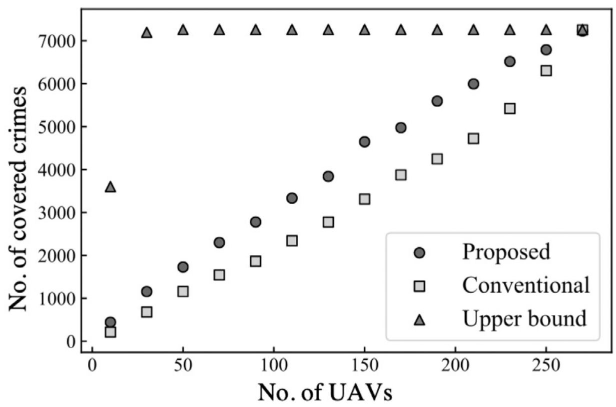
major crimes at blocks 1, 2, $\cdots L$ are represented as $X = (x_1, x_2, \cdots x_L)$ and $Y = (y_1, y_2, \cdots y_L)$, respectively, where L is the total number of blocks. Since this crime data is time series data, X and Y at time t can be represented as $X(t)$ and $Y(t)$. In Fig. 4, as the time shift in the horizontal axis increases, we see the correlation of minor crimes with major crimes in the future. The vertical axis is normalized so that it becomes 1.0 when time shift is zero. As seen in this figure, there are strong correlations between minor and major crimes in each block when Δt is 6, 12, and 24 hours. However, when Δt is 1 hour, the cross correlation become negative for some shifted times.

In the simulation, we assumed that the server is functional enough to detect minor offences that occurred in a block if a UAV acquires crime-related sensor data in that block. The integration of the information collected by our system and other policing systems such as 911 [51] may be used to ensure the detection of minor offences, which is a form of the multi-modal methods introduced in Section 2. More concretely, on the basis of the number of minor offences over the latest ten control cycles, the server predicts the number of major offences at the next control cycle. The number of minor offences in blocks where UAVs acquire no data is assumed to be 0. We also assume that the time taken for prediction is negligible compared with Δt.

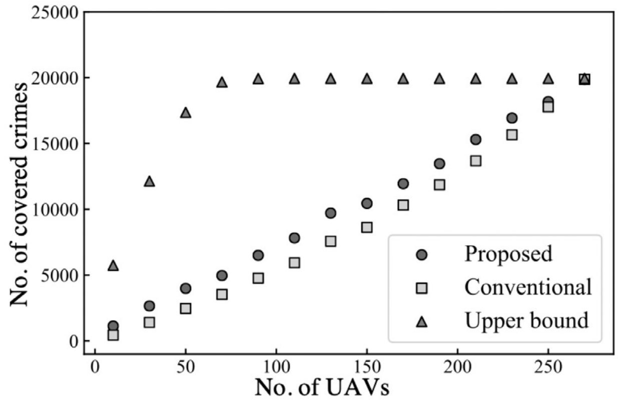
The metric we adopted in our evaluation is the number of crimes that occurred in the areas covered by UAVs; if it is large enough compared to the total number of crimes, UAVs are allocated for crime deterrence. However, we should consider the flying time of each UAV as temporal overhead when we calculate the number of crimes covered by UAVs. When K is one, each UAV flies back and forth between the home position and its allocated block for each control cycle. The number of covered crimes based on the data acquired by UAV u during T_i is defined as

$$N_{l_u}^{i,k} \times \frac{\Delta t - 2(H_u - L_u)/v}{\Delta t}, \tag{6}$$

where v denotes the average flying speed of UAV u and l_u denotes the block assigned to it. H_u and L_u denote the home position of UAV u and the position of l_u, respectively. Considering the realistic specifications of a recently commercialized UAV[52], we set v to 15 m/s. There are 22 districts in the area, each of which has a police station. We assumed that the position of the police station corresponds to the home position and when each UAV flies to each block, it starts flying from



(a) Periods of dataset for learning and prediction were Jan. 2014–July 2015 and Aug. 2015–Dec. 2015.



(b) Only dataset of crimes that occur outside of buildings was considered. Periods of dataset were same as in Figs. 5 and 6.

Fig. 7. Total number of crimes covered by UAVs vs. number of UAVs. Δt was set to 12.

Table 4
Parameters of LSTM.

Parameter	Value
Number of hidden units	100
Activation function	Linear
Optimizer	Adam
Number of epochs	50
Batch size	100
Loss function	Mean squared error
Input time length	10

the police station of the district that includes the block and returns there for Δt. The position of each block is also assumed to be at the center of gravity of a polygon representing the block in Fig. 3.

4.2. Machine learning technique

This section discusses the machine learning method and feature selection method used in the simulation. We used Python and its libraries for this implementation. We adopted LSTM as the machine learning method because it is known to be suitable for predicting time series data [53,54]. Table 4 lists the parameters of LSTM. The LSTM method uses the Keras [55] neural network library for its implementation. In our simulation, the model has 100 LSTM units as the first hidden layer, and they are fully connected to the dense layer. The output is activated by the linear function. The model is trained

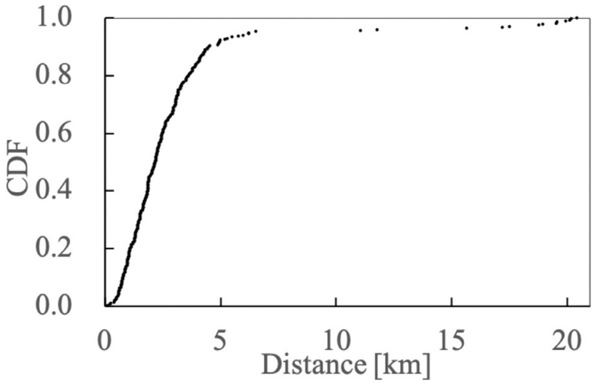


Fig. 8. Cumulative distribution function of flying distance.

by the Adam optimizer with 50 epochs and a batch size of 100. All other parameters were set to the default values of the library. The prediction model changes for each simulation.

We used a perturbation method for the feature selection. This method evaluates the effect of small changes in each input on the neural network output [56]. The algorithm adjusts one of the input variables while keeping all the others unchanged. The acquisition metric, I_l^i, is calculated from the responses of the output variable against each change in the input variable.

By using the root mean square error (RMSE), I_l^i is given as

$$I_l^i = \left(RMSE\left(y, y_{pred}\right) - RMSE\left(y, y'_{pred}\right)\right)^2, \tag{7}$$

where y, y_{pred}, and y'_{pred} denote the number of actually recorded crimes, the original number of predicted crimes, and the number of crimes predicted from the input values changed by the perturb method, respectively. The physical dimensions of the first and second terms in (5) are identical, since I_l^i is defined using RMSE. In the simulation, we gave 50% increase to each input value one by one to measure I_l^i for all block $l \in L$ and for all control cycles i.

4.3. Results

Figure 5 plots the total number of crimes covered by UAVs against the weight, w. As shown in Fig. 5(a), (b), (c), and (d), Δt was 1, 6, 12, and 24, respectively. The reason the horizontal axis is plotted logarithmically is that the first term in (5) becomes larger by 10^4 than the second term. The plots were obtained by averaging the results obtained from three trials. In (5), as w becomes closer to 1, the server allocates UAVs with more emphasis on the deterrent metric than on the acquisition metric. In contrast, as w becomes closer to 0, the server allocates UAVs with more emphasis on the acquisition metric.

The total number of crimes that actually occurred in the simulation was 7,857. If all input data for prediction is available, the predicted number of crimes was 118,294, 7,066, 6,050, and 6,630 when Δt was 1, 6, 12, and 24, respectively. This suggests that, if Δt is set too short (i.e., to 1), prediction is not accurate, which we can see from the results in Fig. 4.

As shown in Fig. 5, the total number of crimes covered by UAVs significantly decreased when w is 1. This is because patrolling without considering the acquisition metric leads to a decrease in the prediction accuracy, and the number of crimes covered by UAVs eventually decreases. It is important to consider even the slightest acquisition metric because setting w to a value other than 1 increases the total number of crimes covered by UAVs. The results in Fig. 5 suggest that using our framework for operating the UAVs could help deter around 4,500 cases of crime, which is a sufficiently large portion of the 7,857 cases of the total number of crimes. These results demonstrate the effectiveness of the UAV allocation considering not only the deterrent metric but also the acquisition metric.

Figure 6 (a), (b), (c), and (d) plots the total number of crimes covered by UAVs against the number of UAVs with $\Delta t = 1$, 6, 12, and 24, respectively. We compared three types of allocation: the proposed framework, a conventional one, and upper bound. In the proposed framework, the server allocates UAVs considering both the deterrent metric and the acquisition metric. We examined the proposed framework with $w = 10^{-5}$. In the conventional one, the server allocates UAVs using the deterrent metric without considering the acquisition metric at all, which corresponds to $w = 1$ in (5). In the upper bound, the server allocates UAVs such that the number of crimes covered by UAVs is always the maximum in each control cycle, assuming that the number of crimes that will occur in all blocks in the future is ideally known beforehand; the total number of crimes covered by UAVs takes the upper limit value.

As shown in Fig. 6, with the upper bound, the total number of crimes covered by UAVs takes the maximum value even when the number of UAVs is small. On the other hand, as Δt becomes larger, the total number of crimes covered by UAVs becomes smaller when the number of UAVs is as small as 10 or 30. This is because when UAVs fly frequently, like $\Delta t = 1$, they can cover many blocks with a small number of UAVs, while as Δt increases, the number of blocks that cannot be covered increases. In both the proposed framework and the conventional one, as the number of UAVs increases, the total number of crimes covered by UAVs monotonically increases. This is obviously because as the number of UAVs increases, the number of blocks that UAVs can patrol increases. Compared with the 7,857 crimes that actually occurred, the upper bound reached that number in most cases, and the proposed framework and the conventional one came close to it when the number of UAVs was close to 250. As shown in Fig. 6(a)–(d), the proposed framework worked to increase the expected number of crimes deterred by UAV patrolling more than the conventional one, except in regions where the number of UAVs was extremely small or large.

4.4. Other datasets

Next, we show the results obtained using two additional datasets. The first one consists of minor and major offences as input and output data, the same as in the dataset used for obtaining the results in Figs. 5 and 6, but the periods of the dataset for learning and prediction are Jan. 2014–July 2015 and Aug. 2015–Dec. 2015, respectively. The second one only considered crimes that usually occur outside of buildings, which include burglary, motor vehicle theft, robbery, and criminal trespass, and they are used as both input and output data. The learning and prediction periods are the same as the dataset used for obtaining the results in Figs. 5 and 6. Using these datasets, we plot the total number of crimes covered by UAVs versus the number of UAVs in Fig. 7(a) and (b). Δt was set to 12. In these figures, we see basically the same trend as in Fig. 6(c), in which the dataset in Table 3 was used and Δt was set to 12; the proposed framework performed better and closer to the upper bound than the conventional method. Evaluating using the three datasets has made the superiority of the proposed framework convincing.

4.5. Real-world feasibility of simulation scenario

On the basis of our analysis thus far, this section explores the feasibility of the simulation scenario we assumed in the evaluation, which helps when considering the practical application of the proposed framework. The discussion revolves around two issues: energy consumption and the relationship between data analysis and crimes.

To estimate the amount of energy consumed in each operation, we plot the cumulative distribution function of one-way flying distance between each block and its home position (Fig. 8). As shown in the figure, 92.2 % of one-way flying distances were shorter than 5 km, while the longest distance was around 20 km. According to the specifications of a UAV recently commercialized by Bell Textron Inc. [41], it is capable of flying autonomously and can cover a distance of approximately 56.3 km in 30 min with a single battery charge. Once UAVs arrive at the block, they may stay at nearby stations pre-installed on buildings for surveillance to save energy. Those stations may be equipped with battery charging or replacement functions [57,58]. Given these parameters, we can safely assume that our simulation scenario is not far from reality with respect to energy consumption.

Adaptive change of the behavior of criminals is another issue that requires consideration. Offenders might change their behavioral patterns (or commit new types of crimes never observed before) in response to the operation of UAVs, especially if the pattern of their deployment is informed by the predictive model to deter crime. This means that the prediction model may need to be updated to adapt to changes in the patterns of criminal behavior, which is a common issue across many types of predictive operations that use machine learning [59]. As discussed in our evaluation of the results, the proposed framework works well as long as there is a correlation between the input data and the output data used for prediction. In other words, the proposed framework should be used only when such correlation is clearly observed. Particularly, to apply the proposed framework to new types of crimes, input data correlated to those crimes needs to be discovered. During the period where the correlation between input and output for the prediction model is not confirmed, UAVs should be allocated with no prediction and in accordance with the cumulative crime counts from the past. As mentioned in Sect. 2, performance testing of the data analysis stage itself, including correlation analysis, is outside the scope of this paper. Other researchers (e.g., Arietta et al. and Beiji et al.) have worked on the correlation analysis between crime-related visual data and crimes that actually occurred [25,26].

5. Conclusions and future work

We have proposed a multi-UAV allocation framework that allocates UAVs to acquire data for improving the performance of subsequent crime prediction while maintaining the possibility that UAVs cover areas where crimes are likely to occur. Through a literature review, we have confirmed the novelty of the proposed framework; the existing works on UAV allocations did not consider predictive policing. Also, our work is clearly differentiated from the other by its contributions to the problem formulation of multi-UAV allocation, prediction using machine learning, data importance extraction, simulation using a real dataset, and discussion of energy analysis. A simulation study using a real dataset has demonstrated that the proposed framework works well in terms of the number of crimes covered by UAVs as long as there is a correlation between the input data and the output data used for prediction like when $\Delta t = 6$, 12, and 24. The results have also verified that the proposed framework performs more closely to the upper bound than the conventional method, which considers the deterrent metric only without any prediction. We have also demonstrated the robustness of the proposed framework in an evaluation using multiple datasets. We have confirmed the realism of the simulation in terms of energy consumption from the analysis of the distribution of one-way flying distance of UAVs.

Future research directions will be summarized as follows. Data acquired by visual and audio sensors in residential and commercial areas should be analyzed in the context of predictive policing. Correlation between information extracted from the data such as darkness, quietness, and the number of people and crime occurrence should be verified from an integrated analysis with the data provided by other policing systems such as 911 [51]. Communication and computing resources required for the proposed framework should be also studied. To estimate energy consumption of the proposed framework more accurately than in this paper, an evaluation model that emulates the non-linear characteristics of energy consumption [60] for sensing and flying more realistically should be established through experimental measurement.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

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