This article has been accepted for publication in IEEE Network. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/MNET.2025.3580847

A Sustainable 3D Cube Surveillance and Pedestrian Monitoring Framework for Green AI Theme Park

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***Abstract*—Recently, the concept of Green AI is expanding its applicability to various academic and industrial fields including surveillance with energy efficiency, maximum reliability, managing traffic flows in smart cities. In particular, it is highly expected that the sustainable 3D cube surveillance is applied to theme park environment with Green AI perspective appropriately. In this paper, we design a sustainable 3D cube framework for surveillance and pedestrian monitoring toward Green AI-enabled theme park environment using mobile robots and smart UAVs. Then, a main research problem is formally defined. To resolve the problem, three different approaches are proposed with 3D zone-based and energy-efficient rearrangement strategies. Moreover, the performance of the proposed schemes is evaluated based on experiment outcomes which are obtained from expansive simulations with various scenarios.**

***Index Terms*—Green AI, mobile robot, UAVs, 3D cube**

I. Introduction

TODAY, the mobile robot field is one of the rapid expansion areas for the various purposes in smart cities. Thanks to Mobile robot's recent advancement and promising applicability, it is highly expected that that mobile robots are able to support humans' works and hard tasks in numerous fields regarding to AI (Artificial Intelligence), machine learning technologies covering IoT (Internet of Things), surveillance, urban mobility, planetary exploration, patrols, distributed systems, emergency rescue operations, reconnaissance, and industrial automation, personal service, extreme environment, transportation, big data, medical care, etc [1], [2], [3], [4], [5]. And, application utilization, sensor information, cognitive ability is processed properly by high-quality robot software recently.

Also, as another admirable system component in smart cities, UAVs (Unmanned Aerial Vehicles) are widely utilized for numerous applications. So, UAVs can achive military missions, rapid movements to specific areas that are difficult for humans to access directly, disaster detection, crime prevention, traffic monitoring, target tracking, virtual emotion surveillance, intelligent transportation system, etc [6], [7], [8], [9]. And, it has been used for geographical data and is also used in agriculture. UAV sales are on the rise thanks to low prices and numerous fields of use. Basically, UAVs can record not only 2D (2-Dimension) space but also large-scale topography in a 3D (3-Dimension) environment. If these mobile robots and UAVs are worked in cooperation, it is highly anticipated that they can support a more complex environment with high accuracy and a wider range than individual applicability. Therefore, it is indispensable to deliberate on mobile robots and UAVs together in order to complete the requested missions, tasks in a wide range of environments successfully.

On the other hand, many researchers studied how to construct barriers in 2D space and how to locate several types of barrier members. Barriers include movable devices or static components to achieve various objectives covering surveillance, monitoring specific districts, virtual emotion surveillance, [10], [11]. Such a 2D barrier plays an important role in games, self-driving cars, and indoor location tracking systems on the plane depending on how to generate those 2D barriers to fit with the pursuing goals and the given requirements such as maximum lifetime of barriers, minimum number of barrier members, maximum detection accuracy, minimum movement of mobile components, obstacle-aware constructions, etc. However, there is a limit if various factors such as the size and shape of the object in 2D environment are not considered. For previous studies in 2D space, the volume occupied by nodes and communication ranges was generally negligible, and the depth of the given area was not covered for 2D barriers construction so that the existing solutions of 2D barriers can not apply the critical tasks in 3D space as well as not transform into relevant research problems directly. Unlike a 2D plane where the barrier covers from one side to the other, it is necessary to consider a broad range of 3D environment. Generally, when compared to 2D space, 3D environment is more difficult to design and to create energy-efficient 3D surveillance framework because 3D space originally causes diverse features, constraints, factors to be considered strictly. It follows that 3D-based surveillance and barrier essentially requires more complex mathematical models and algorithms with improved performance of computational complexity, storage space complexity, calculation time, etc. Hence, it is vital to consider how to design 3D cube surveillance system with sustainable construction or persistent management.

AI-enabled methods and technologies covering machine learning and deep learning are expanding tremendously to a large scale fields, applicable systems and research branches including semantic communication, autonomous vehicles, tactile internet, IoT system, 5G and 6G communications, theme park environments, amuse attraction analysis, etc. Particularly, the important concepts of *Red AI* and *Green AI* were proposed recently by [12]. The *Red AI* mainly focuses on improvements of implementation accuracy, executable task speed, minimal delay, maximum achievement with a consideration of massive training data set, number of floating-point operations, computational costs and so on. On the other hand, *Green AI* pursues to how to satisfy on environment features, social costs, economic factors, eco-friendly issue by estimating carbon emission, electricity, training time efficiency, inference energy efficiency, etc. Furthermore, the issues and topics of energy-efficient green computing, sustainable system, crowdsensing, environmental science, renewable energy sources have attracted much interests of researchers [13], [14], [15]. Accordingly, we should conduct a promising research of Green AI-assisted theme part environment for sustainable surveillance.

Based on the above observations and motivations, the primary contributions and technical contents of this paper are summarized as follows.

- Firstly, we design a sustainable 3D cube framework for surveillance and pedestrian monitoring for Green AI-enabled theme park environment with a collaboration of mobile robots and smart UAVs. The proposed system supports energy-efficient management, secure service, sustainable surveillance to users. Also, the system overview, settings, assumptions and key terms are specified in detail.
- Then, the research problem of minimizing uncovered volume by a combination of mobile robots and smart UAVs in sustainable 3D cube space is formally represented.
- To solve the defined problem, three different schemes are proposed supported by essential strategy with divided zones of 3D cube space so that the sustainable 3D cube surveillance with energy-efficiency and detection accuracy is accomplished.
- Furthermore, the devised schemes are performed through extensive simulations with practical scenarios and various settings and their performances and measurements are evaluated based on numerical outcomes with detailed discussions and demonstrations.

The basic organization of this paper is as follows. Section II describes the sustainable 3D cube framework for surveillance and pedestrian monitoring in Green AI-enabled theme park environment including system settings, assumptions, key terms, problem definition with ILP formulations. Then, in Section III, three different algorithms are presented in detail. Also, in Section IV, the performance analysis of the developed methods is conducted through numerical results which are obtained from expansive experiments. Consequently, the paper is concluded in Section V.

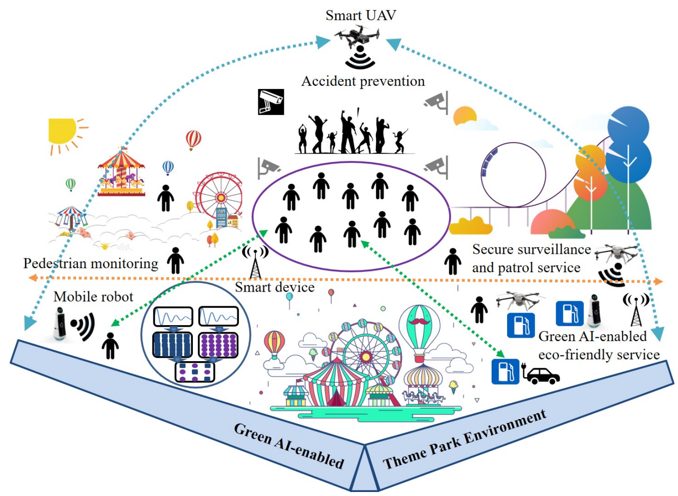


Fig. 1. A brief example of sustainable surveillance and pedestrian monitoring in Green AI-enabled theme park environment.

II. Proposed Framework

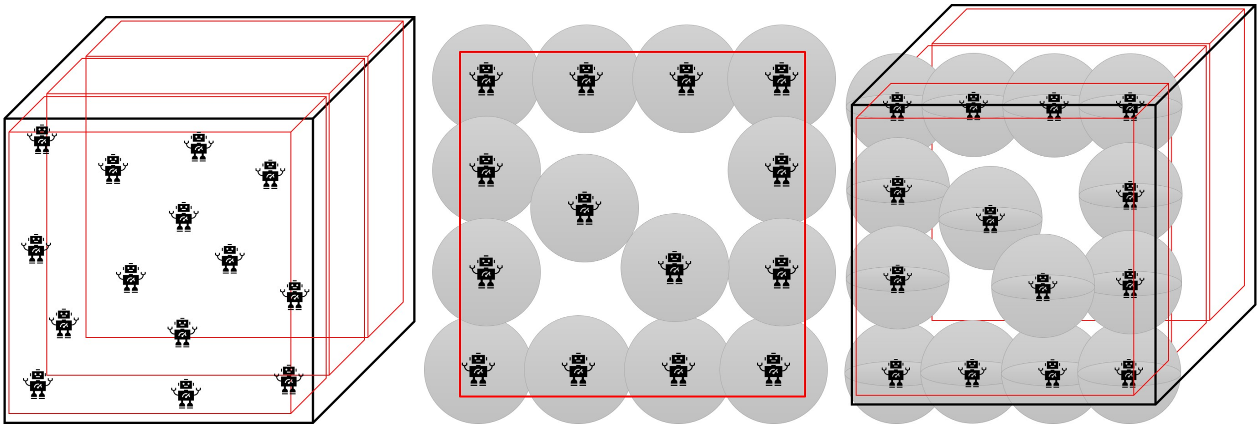
In this section, we specify the proposed framework of 3D cube surveillance and pedestrian monitoring framework including system settings, design features, assumptions, whole overview, notations, essential terms, problem definition.

A. System Settings, Design Features and Assumptions

First, for system conditions, when there is a given 3D zone and there is another zone divided into three cubes, the area that the communication range could not cover is minimized. The first condition is to make all component communications the same. By making them all the same, the calculation process becomes easier, and the consideration is reduced. It should also be adjusted so that this communication range is not larger than the given area. And the total number of system components should be limited. This is because this method cannot be said to be efficient if the simulation results are good using a lot of components without restrictions. Finally, a limit is set on the movement distance of the component.

In summary, the following system settings, design features and assumptions are applied to the proposed environment.

- The proposed framework covers cube as the given 3D area for theme park applications and attractions.
- The proposed system components are consist of mobile robots for the ground side and smart UAVs for the aerial side in cube environment.
- For the given 3D theme park space, each divided plate has equal size when the dividing strategy is implemented.
- The communication range of each component is set to be the equal.
- While the moving trajectories of mobile robots are ground sides of cube, the preferred trajectories of smart UAVs are aerial sides to complete the given tasks.



(a) Verifying random locations of initial mobile components (b) Applying periphery domination strategy into 2D plane (c) Executing periphery domination strategy into 3D environment

Fig. 2. Algorithm 1: *Periphery-Domination-Preference*: The initial status and execution strategy.

B. System Overview

Now, we display the whole overview of sustainable 3D cube surveillance and pedestrian monitoring system in Green AI-enabled theme park environment. Basically, there are various attractions, admission entrances, crowd of users, pedestrians and staffs, a millions of smart devices in amusement or theme park regions. To provide energy-efficient management, secure service, sustainable surveillance to users, the proposed system pursues the applicability of Green AI supported by mobile robots in the ground side and smart UAVS in aerial or upper side in the given 3D cube theme park space. It follows that the proposed framework seeks various critical system tasks including screening or security checks, accident warnings to users, attraction status checks, disaster managements, emergent item delivery, criminal prevention, pedestrian tracking by the perspective of sustainable Green AI-assisted 3D cube theme park environment.

Fig. 1 depicts a brief application example of sustainable surveillance and pedestrian monitoring in Green AI-enabled theme park environment. As it can be shown in Fig. 1, the system components including mobile robots, smart UAVs and smart devices are able to support the secure surveillance and pedestrian monitoring with Green AI-assisted eco-friendly service in theme park environment.

C. Key Terms and Problem Definition

The key terms and critical definitions for the proposed sustainable 3D cube theme park system are represented as follows.

Definition 2.1 (Green AI-enabled theme park space): The Green AI-enabled theme park space, called as *GreenAIThemePark*, pursues to provide the environmental, eco-friendly, energy-efficient services, optimal social managements and secure attractions supported by various types of system components covering mobile robots, smart UAVs, autonomous systems, IoT devices with a consideration of estimating electricity usage, carbon emissions, time efficiency and other possible eco-friendly factors.

Definition 2.2 (Sustainable 3D cube surveillance): Suppose that there exist the targeted cube-shaped space, the group of mobile components including the set of mobile robots, the set of smart UAVs. The sustainable 3D cube surveillance, called as *Sustain3DSurv*, is to supply the continuous detection of penetrations and requested objects with sustainable, energy-efficient management appropriately in 3D cube space.

Also, the main research problem is specified as follows.

Definition 2.3 (Sustainable 3D cube surveillance remnant minimization volume problem): It is a given that a set of mobile robots, a set of smart UAVS with homogeneous ranges have been located randomly in cube-shaped theme park space initially. The sustainable 3D cube surveillance remnant volume minimization problem, referred as *Min3DSurvRem*, is to minimize the remnant undetectable volume such that the limited movement distance of mobile robots and UAVs are satisfied and the required minimum number of *Sustain3DSurv* is created completely.

III. Proposed Schemes

In this section, we describe three different algorithms which are proposed to reduce the amount of undetectable space volume in 3D cube. A description of the execution procedures for all algorithms is presented in detail.

A. Algorithm 1: Periphery-Domination-Preference

Firstly, we specify the first algorithm, referred as *Periphery-Domination-Preference*. Its basic strategies, procedures and execution steps are presented as follows.

- Identify 3D cube Green AI-enabled theme park space.
- Accept a set of mobile components including mobile robots and smart UAVs with their detection range as well as verify randomly scattered locations of within Green AI-enabled theme park space.
- Set a set of mobile components as the potential candidate set for sustainable movement.
- Divide 3D cube space into three planes vertically or horizontally.

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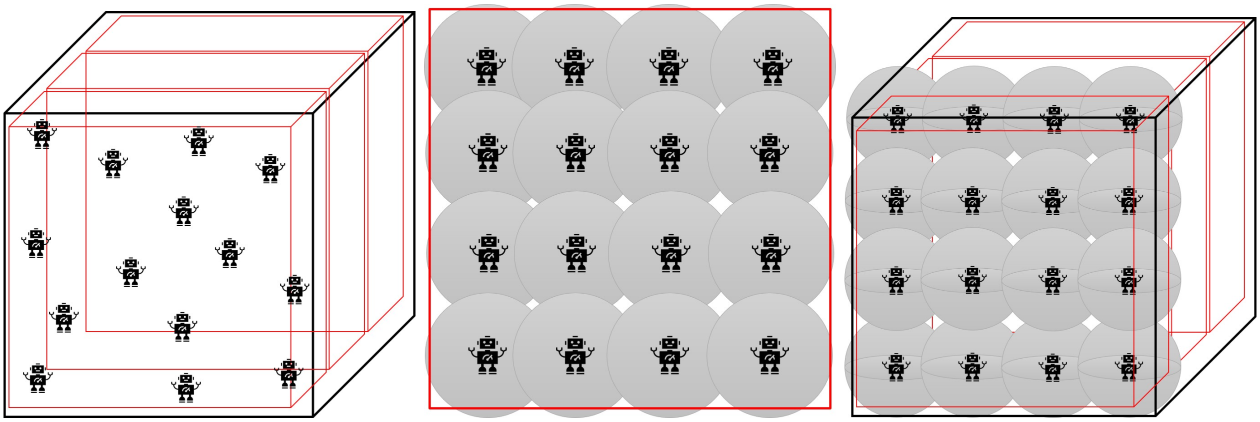

(a) Identifying random positions of initial mobile components (b) Applying minimal overlap strategy orderly into 2D plane (c) Expanding minimal overlap strategy into 3D space

Fig. 3. Algorithm 2: *Minimum-Overlap-Configuration*: The initial state and operation strategy.

- The following sub-steps are implemented until the requested number of *Sustain3DSurv* is equipped with 3D cube space.
  - Move available components from potential candidate set into periphery of the divided plane with movement limit as many as possible.
  - Check if *Sustain3DSurv* is created at every plane. If so, stop current iteration.
- Estimate the remnant volume ψ which is not detected by the formed *Sustain3DSurv*.
- Return ψ as final outcome.

Fig. 2 shows the initial status and execution strategy of Algorithm 1: *Periphery-Domination-Preference*. Fig. 2(a) depicts the identification of initial mobile components locations for mobile robots and smart UAVs. Fig. 2(b) stands for the execution status of applying periphery domination preference strategy into the divided 2D plane. And, Fig. 2(c) presents the implementation status of 3D cube by the available mobile components through periphery domination preference strategy.

B. *Algorithm 2:* Minimum-Overlap-Configuration

Secondly, we explain the second algorithm, called as *Minimum-Overlap-Configuration*. Its basic idea is to configure mobile components with a consideration of minimal overlapped detection ranges or minimal wasted room when *Sustain3DSurv* are built in 3D cube Green AI-enabled theme park space. Then, its strategies, procedures and operations steps are provided below.

- Check 3D cube Green AI-enabled theme park space.
- Recognize a set of mobile components, its detection range and initial positions in 3D cube space.
- Initialize a set of mobile component as the potential candidate set for sustainable movement.
- Split 3D cube space into three planes perpendicularly or horizontally.
- The following sub-procedures are performed until the required level of *Sustain3DSurv* is installed in 3D cube space.
  - Draw virtual squares in order for each plane where the length of square fits with the detection range with minimal overlap and its center position is included in the set of potential position.
  - Move available mobile components in the potential candidate set to the centers of virtual squares with movement limit in order.
  - Confirm if *Sustain3DSurv* is constructed at every plane. If so, go out current iteration.
- Calculate the remnant volume ψ that is not covered by the found *Sustain3DSurv*.
- Return ψ as final result.

Fig. 3(a) expresses the initial state and operations steps of Algorithm 2: *Minimum-Overlap-Configuration*. Fig. 3(b) depicts the status after the minimal overlap strategy is implemented with 2D plane view. Also, Fig. 3(c) displays the executed status of minimal duplicated space with 3D expanded view, which are supported by the definite movements of mobile components at every plane.

C. *Algorithm 3:* Combined-Sustainable-Adjustment

Lastly, we propose the third algorithm, referred as *Combined-Sustainable-Adjustment* whose essential strategy is the combined implementation of Algorithm 1 and Algorithm 2. It follows that the devised *Combined-Sustainable-Adjustment* utilizes the sustainable adjustment strategy through differential executions with the adjustment of usage ratio according to divided planes in 3D cube Green AI-enabled theme park space. Then, its procedures and operations steps are explained as follows.

Fig. 4(a) manifests the status of slicing 3D cube to three different planes with unique identification number where the second plane is positioned at center side of 3D cube for Algorithm 3: *Combined-Sustainable-Adjustment*. Fig. 4(b) shows the the first half execution status of Algorithm 3. It follows that the first plane and the third plane are operated by Algorithm 1. Also, the second plane is implemented by Algorithm 2. On the other hand, Fig. 4(c) presents the second half implementation status of Algorithm 3 with the reverse order. That is, the first

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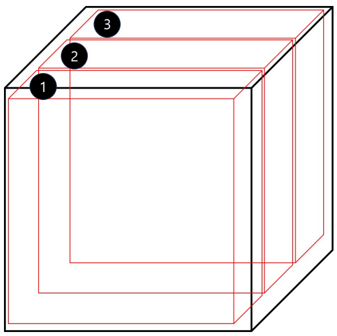
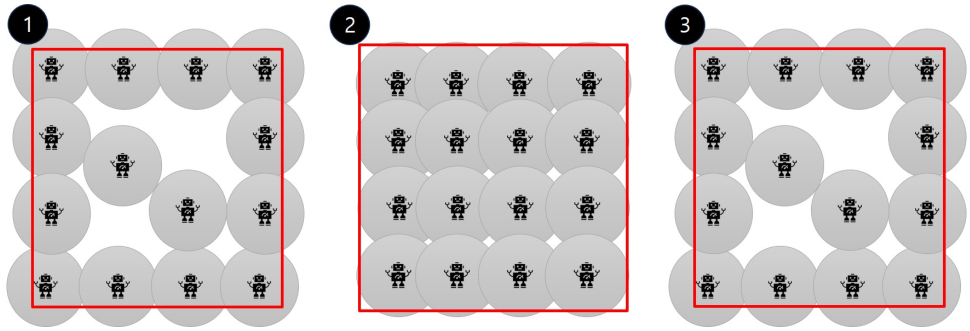
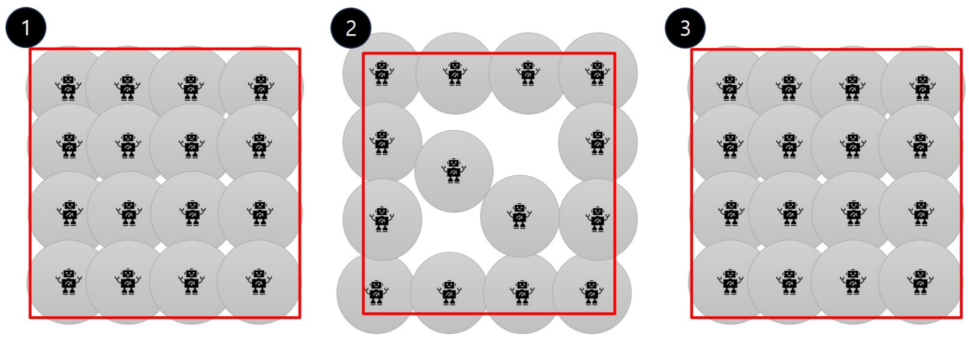


(a) Slicing 3D cube to three different planes unique identification number in Algorithm 3



(b) The first half execution status of Algorithm 3. The first, third planes applied by Algorithm 1 and the second plane operated by Algorithm 2



(c) The second half fulfillment status of Algorithm 3. The first, third planes implemented by Algorithm 2 and the second zone managed by Algorithm 1.

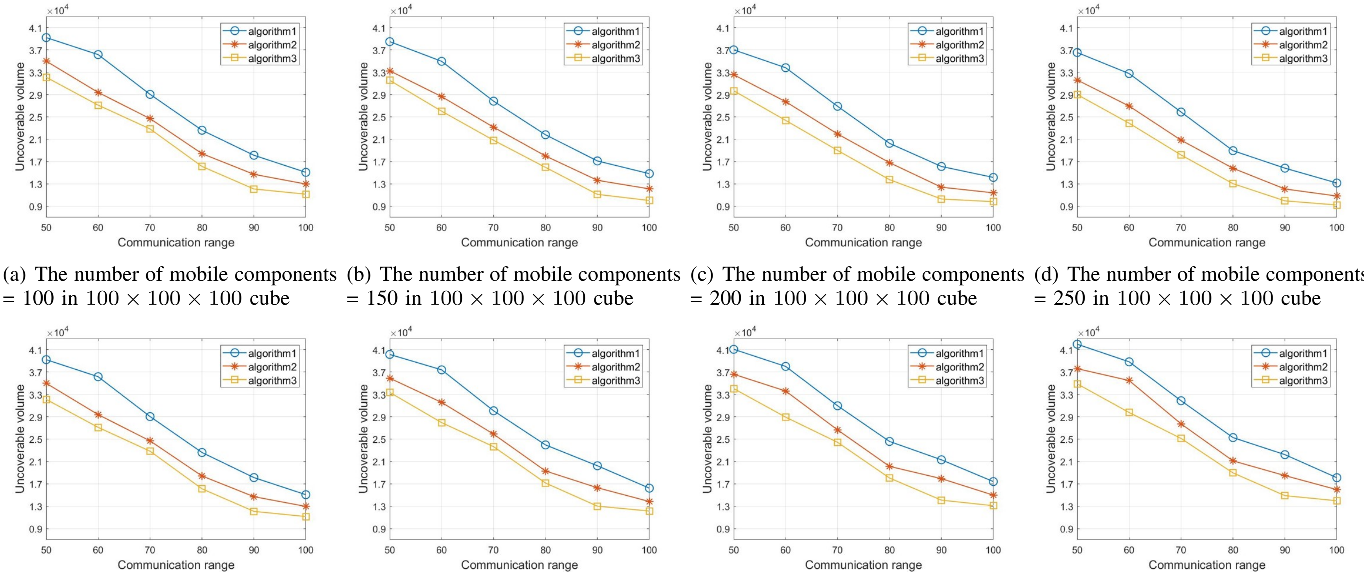
Fig. 4. Slicing 3D cube and the first half, the second half applicable status of Algorithm 3.

plane and the third plane are applied by Algorithm 2 and the second plane is practiced by Algorithm 1.

- Verify 3D cube Green AI-assisted theme park space.
- Acknowledge a set of mobile components with the sensing range r and check their initial locations in 3D cube Green AI-assisted theme park space.
- Set the potential candidate set for sustainable movement.
- Slice 3D cube area into three planes perpendicularly or horizontally as well as confirm each plane with unique identification where the second plane is located at center side of cube.
- The following sub-steps are implemented until the first potential remnant volume is earned.
  - Call Algorithm 1 and execute it for the first plane and the third plane.
  - Call Algorithm 2 and perform it for the second plane.
  - Estimate the potential remnant volume and set it as the first value.
- The following sub-steps are operated until the second potential remnant volume is obtained.
  - Call Algorithm 2 and carry out it for the first plane and the third plane.
  - Call Algorithm 1 and fulfill it for the second plane.
  - Calculate the potential remnant volume and update it as the second value.
- Compare the first potential remnant volume with the second potential remnant volume and update the smaller one as ψ.
- Return ψ as final outcome.

IV. Experimental Evaluations

In this section, the developed Algorithm 1: *Periphery-Domination-Preference*, Algorithm 2: *Minimum-Overlap-Configuration* and Algorithm 3: *Combined-Sustainable-Adjustment* are demonstrated relying on the earned results through expansive simulations with various settings, parameters and scenarios including several number of mobile components, different 3D cube theme park spaces, communication or detection ranges, interval for random detection radii, the requested number of *Sustain3DSurv*, etc. It is noted for simulation execution environment that the size of 3D cube as theme park space are utilized as 100 (width) by 100 (depth) by 100 (height) meter, 150 by 150 by 150 meter, 200 by 200 by 200 meter, 200 by 200 by 200 meter, respectively. And, the total number of mobile components including mobile robots and smart UAVs is ranging from 100 through 250. Also, the interval of random detection radii by mobile components are used between 30 and 45. Furthermore, it is specified that every numerical acquisitions of the remnant or uncoverable volume of ψ as the final objective value must be the average value of 1000 different simulation environment settings and parameters. Entirely, our simulations for sustainable 3D cube framework for surveillance and pedestrian monitoring for Green AI-enabled theme park are composed of four different groups where each group has own critical features, requirements and parameters.



(a) The number of mobile components = 100 in $100 \times 100 \times 100$ cube
(b) The number of mobile components = 150 in $100 \times 100 \times 100$ cube
(c) The number of mobile components = 200 in $100 \times 100 \times 100$ cube
(d) The number of mobile components = 250 in $100 \times 100 \times 100$ cube
(e) The number of mobile components = 100 in $150 \times 150 \times 150$ cube
(f) The number of mobile components = 150 in $150 \times 150 \times 150$ cube
(g) The number of mobile components = 200 in $150 \times 150 \times 150$ cube
(h) The number of mobile components = 250 in $150 \times 150 \times 150$ cube

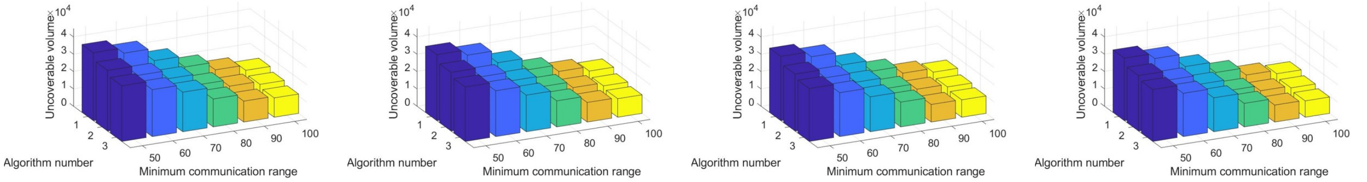
Fig. 5. Remnant volume of ψ by various number of system members n and communication ranges in $100 \times 100 \times 100$, $150 \times 150 \times 150$ cube environment.

About the first experiment setting, we execute three different algorithms, Algorithm 1: *Periphery-Domination-Preference*, Algorithm 2: *Minimum-Overlap-Configuration* and Algorithm 3: *Combined-Sustainable-Adjustment* with different number of mobile components in Green AI-enabled theme park size of $100 \times 100 \times 100$ as shown in Fig. 5. We confirm that for the first group of experiments, the performance result graph is composed of two axis. It follows that X-coordinate axis expresses the homogeneous communication or detection range of mobile components and Y-coordinate axis stands for the remnant uncoverable or undetectable volume ψ. Also, on the performance graph in group 1, Algorithm 1 is marked with circle marker with solid line, Algorithm 2 is displayed with star marker with solid line as well as Algorithm 3 is represented with square marker with solid line, respectively. Fig. 5(a) and Fig. 5(b) demonstrate the outcome of those devised algorithms if the total number of mobile components is 100 and 150 within $100 \times 100 \times 100$ theme park space. Also, as it can be seen in Fig. 5(c) and Fig. 5(d), they verify the obtained results when the settings and parameters with n = 200 and n = 250 are applied to $100 \times 100 \times 100$ 3D space. Then, as seen in Fig. 5, we are able to demonstrate that not only the remnant undetectable volume ψ is decreasing for all algorithms basically as the communication range is increasing but also the performance of Algorithm 3: *Combined-Sustainable-Adjustment* outperforms other algorithms clearly.

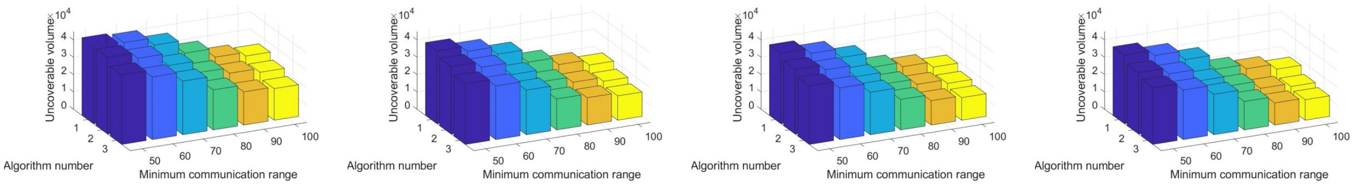
For the second simulation scenario, three different schemes are performed with the total number of mobile components = 100 according to various Green AI-assisted theme park space sizes as it can be seen in Fig. 5. Fig. 5(e) and Fig. 5(f) verify the result of three different methods for Algorithm 1: *Periphery-Domination-Preference*, Algorithm 2: *Minimum-Overlap-Configuration* and Algorithm 3: *Combined-Sustainable-Adjustment* when $100 \times 100 \times 100$ and $150 \times 150 \times 150$ are given as Green AI-enabled theme park size. And, Fig. 5(g) and Fig. 5(h) show the outcomes if $200 \times 200 \times 200$ and $250 \times 250 \times 250$ are put into the simulation settings. As it can be checked in in Fig. 5, we can confirm that the remnant undetectable volume ψ decreases for every scheme as a whole as the communication range increases and the performance of Algorithm 3: *Combined-Sustainable-Adjustment* is better than others.

As the third group of experiment scenario, it is noted that the performance result graph is displayed with three axis where X-coordinate depicts the homogeneous minimum communication or detection range of mobile components and Y-coordinate describes the remnant uncoverable or undetectable volume ψ that is objective result to resolve the *Min3DSurvRem* problem. In addition, Algorithm number is shown in Z-coordinate. As it is shown in Fig. 6, the random intervals of communication range are set as 30, 35, 40, 35 in this scenario. It follows that Fig. 6(a) and Fig. 6(b) demonstrate the performance of three algorithms with the random interval of detection range = 30, 35. Furthermore, Fig. 6(c) and Fig. 6(d) validate the effectiveness of three algorithms relying on the input of 40, 45 as the random interval of communication radius. Largely, we could affirm that Algorithm 3: *Combined-Sustainable-Adjustment* has the best result when compared with other schemes.

Finally, as the fourth experiment setting, three different methods of Algorithm 1: *Periphery-Domination-Preference*, Algorithm 2: *Minimum-Overlap-Configuration* and Algorithm 3: *Combined-Sustainable-Adjustment* are achieved depending on various requested minimum number of *Sustain3DSurv* as seen in Fig. 6. It is also noted that the fourth experiment setting deliberates on Green AI-assisted theme park space of $100 \times 100 \times 100$ when n = 100 is given. Fig. 6(e) and Fig. 6(f) certify the performance of three algorithms with



(a) Interval of random communication range r = 30 in $100 \times 100 \times 100$ cube (b) Interval of random communication range r = 35 in $100 \times 100 \times 100$ cube (c) Interval of random communication range r = 40 in $100 \times 100 \times 100$ cube (d) Interval of random communication range r = 45 in $100 \times 100 \times 100$ cube



(e) Required *Sustain3DSurv* = 10 in $100 \times 100 \times 100$ cube (f) Required *Sustain3DSurv* = 11 in $100 \times 100 \times 100$ cube (g) Required *Sustain3DSurv* = 12 in $100 \times 100 \times 100$ cube (h) Required *Sustain3DSurv* = 13 in $100 \times 100 \times 100$ cube

Fig. 6. Remnant volume of ψ by various interval of random communication ranges and various required surveillance with n = 100 in $100 \times 100 \times 100$ cube space.

the requested minimum number of *Sustain3DSurv* = 10, 11. Similarly, Fig. 6(g) and Fig. 6(h) stands for the outcome of proposed algorithms given with the requested minimum number of *Sustain3DSurv* = 12, 13. Based on the experiment outcomes by Fig. 6, we confirm that as a whole, the remnant undetectable volume ψ is decreasing as the communication range is increasing for every algorithm. Besides, we ascertain that Algorithm 3: *Combined-Sustainable-Adjustment* outperforms Algorithm 1: *Periphery-Domination-Preference* and Algorithm 2: *Minimum-Overlap-Configuration* for all applied cases consequently.

V. Conclusion

In this paper, we introduce the sustainable 3D cube platform to achieve surveillance and pedestrian monitoring with a collaboration of mobile robots and smart UAVs in Green AI-enabled theme park environment which is converted into 3D cube space. After system overview, settings, basic definitions are presented, the research problem of minimizing undetectable volume by mobile components is formally defined. To resolve the problem, three different algorithms are developed and their performances are evaluated based on the demonstrated numerical outcomes through expansive simulations with various settings and scenarios. As future works, we plan to expand applicable environments including Green AI-assisted smart buildings with underground spaces in regard to autonomous systems. As future issues, we plan to extend the sustainable 3D surveillance to various circumstances including mountainous terrain, underground spaces, decentralized beneficial systems, low-altitude networking.

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