Efficient Deployment of Energy-constrained Unmanned Aerial Vehicles in 3-dimensional Space

Hunsue Lee, Junghyun Oh, Jaedo Jeon and Beomhee Lee
Department of Electrical and Computer Engineering, Seoul National University, Seoul, Republic of Korea

Keywords: Multi-robot Path Planning, Unmanned Aerial Vehicle, Deployment, Energy Constraint.

Abstract: In this paper, we present an efficient approach to deployment for unmanned aerial vehicles (UAVs). For a number of scattered tasks, we aim to minimize the duration of time that all UAVs reach their task locations. In our previous work, we suggested the collaborative deployment algorithm for mobile robots using a carrier robot which transports and deploys the mobile robots. However, the method worked only in 2-dimensional plane where UAV could not be applied. Therefore, this paper extends the previous work on 3-dimensional space and gives the relevant algorithm. Finally, we presents the feasibility of the proposed algorithm by simulation results.

1 INTRODUCTION

As unmanned aerial vehicle (UAV) is widely used, a number of recent study is putting effort into the development of UAV systems in robotics. The advantages of using UAV platform are that the UAV is suitable for large scale operation such as exploration (Sujit and Beard, 2008)(Luotsinen et al., 2004)(Sujit et al., 2009), simultaneous localization and mapping (SLAM) (Caballero et al., 2009), map-building (Yang et al., 2005), search and rescue (Doherty and Rudol, 2007)(Ryan and Hedrick, 2005), and surveillance (Semsch et al., 2009).

On the other hand, the use of multi-robot system (MRS) is unavoidable because the system can provide flexibility, fault-tolerance, robustness, and cost-effectiveness (Yan et al., 2013). To use multiple UAVs, the problem of multi-robot task allocation has to be addressed. However, the general task allocation problem is known to be nondeterministic polynomial (NP) hard, meaning that optimal solutions cannot be found quickly for large problems (Parker, 2008). The deployment problem is also related with the task allocation problem. Therefore, we need to reduce the amount of computation so that the efficient path can be generated within a finite time.

In this study, we use a team composed of two kinds of heterogeneous robots, one carrier robot (CR) and several UAVs, as shown in Figure 1. We assume the CR has enough energy to complete a mission that is transporting and deploying the UAVs.

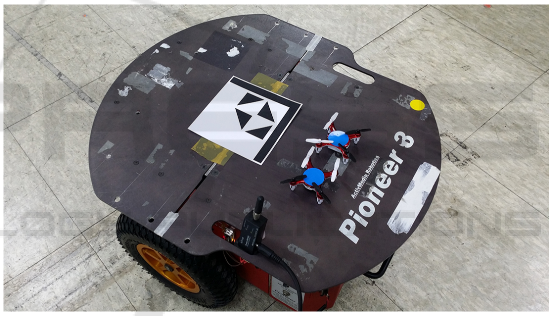

Figure 1: One Pioneer robot as the CR and two X12s as the UAVs. The CR and the UAVs can be recognized and located by using the artificial landmarks.

By using these two kinds of robots, the battery expenditure of the UAV can be reduced and the total travel distance of the UAV can be increased. There are a few studies that use this cooperative strategy (Wang et al., 2015)(Pei and Mutka, 2012)(Rybski et al., 2000)(Saska et al., 2012). However, most of the studies focuses on the mechanical implementation of the system. Only a few existing studies discuss the path planning problem (Mei et al., 2006). Finding the optimal deployment path requires a lot of computation than the amount of computation for the traveling salesman problem (TSP) (Lee et al., 2015b). To reduce the computation, we divided the tasks into several clusters based on the geographical information of the tasks. Then each optimal deployment location for each cluster can be found. Finally, the deployment locations are adjusted and merged into the solution.

Lee, H., Oh, J., Jeon, J. and Lee, B.
Efficient Deployment of Energy-constrained Unmanned Aerial Vehicles in 3-dimensional Space.
DOI: 10.5220/0005986904460451
In *Proceedings of the 13th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2016) - Volume 2*, pages 446-451
ISBN: 978-989-758-198-4

Although the solution does not guarantees the optimality, the efficient path can be generated quickly.

The remainder of this paper is organized as follows. In Section 2, we give brief description of the problem which has been presented in our previous work. In the following section, we address the deployment problem in 3-dimensional space. Then Section 4 describes simulation results. Finally, in Section 5, conclusions are drawn, and areas for further work are discussed.

2 PREVIOUS WORK

2.1 Problem Description

In the given environment, there are m tasks, n UAVs where $n \geq m$, and one CR. The CR's velocity is v_C, constant acceleration and deceleration is a_C, the maximum velocity is v_C^{max}, and the rotating speed is w_C. The UAVs' velocity is v_R and its maximum traveling distance is d^{max}. Unloading of UAVs takes τ seconds. Meanwhile, a task and its location is denoted by q and $\mathbf{v}_q$ respectively.

In the previous work (Lee et al., 2015b) (Lee et al., 2015a), we have formulated the deployment problem for scattered tasks whose objective is to finding the set of optimal deployment points $\mathcal{W}^\star$. Let T_i is the duration of time that the CR moves to α-th deployment location $\mathbf{w}_\alpha$ from the initial location, the CR deploys i-th UAV, and the UAV moves to the target location $\mathbf{v}_{q_i}$. Then T_i is formulated as follows:

$$T_i = \sum_{k=1}^{\alpha} \Big(f(\mathbf{w}_{k-1}, \mathbf{w}_k) + \tau \Big) + \frac{\|\mathbf{w}_\alpha - \mathbf{v}_{q_i}\|}{v_R} \tag{1}$$

By using (1), the objective function can be represented as follows:

$$\mathcal{W}^\star = \arg\min_{\mathcal{W}} \max[T_1, T_2, \dots, T_m] \tag{2}$$

2.2 Path Planning Method

We also proposed a path planning algorithm of the CR. If there are two tasks q_1 and q_2 as shown in Figure 2, we can always find the optimal deployment location w_1 by finding the *circle of Apollonius* O_1 that has given ratio of distances $|v_C^{max}|/|v_R|$ to two given points q_1 and q_2.

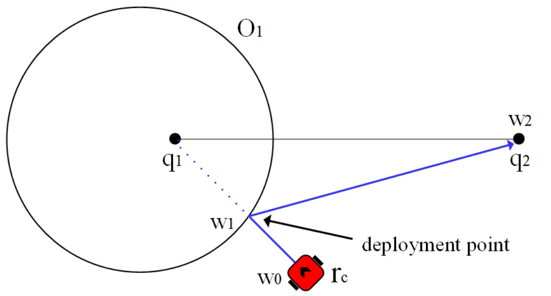

Figure 2: Finding the optimal deployment location w_1 for two given tasks, q_1 and q_2.

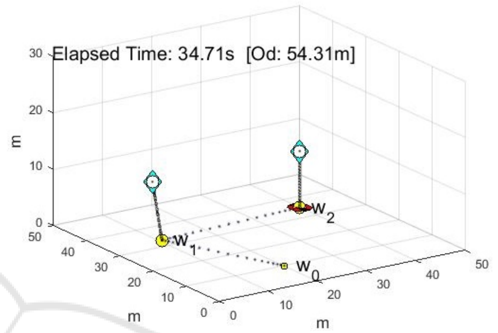

Figure 3: Example of UAV deployment for two tasks in $50m \times 50m \times 30m$ space. We set $v_C^{max} = 10.0m/s, w_C = 2.0rad/s, a_C = 5.0m/s^2, \tau = 1.0s, v_R = 2.0m/s$.

3 UAV DEPLOYMENT IN 3D SPACE

3.1 Optimal Deployment for Two Tasks

First we extends the simulation space into 3D. Figure 3 shows the example of UAV deployment for two tasks in 3D space (W: $50m \times D : 50m \times H : 30m$). In the figure, blue diamonds represent the task location, white circles represent the UAVs, yellow circles represent the deployment locations, and the red rectangle represent the CR. As the CR cannot fly over the ground, the coordinate of the CR is remained in 2D plane. Unless the location of second task is too far, the optimality of the deployment is achieved by letting two UAVs reach their location simultaneously. However, the result in Figure 3 does not satisfy the criterion as the previous algorithm works in 2D plane. Therefore, the deployment location should be adjusted.

Figure 4 describes how the optimal deployment location can be obtained. Let z_1 and z_2 be the heights of the tasks q_1 and q_2 respectively. If $z_1 = 0$ and $z_2 = 0$, then the optimal deployment location w_{1new} for q_1' and q_2' in Figure 4 is calculated by finding Δd

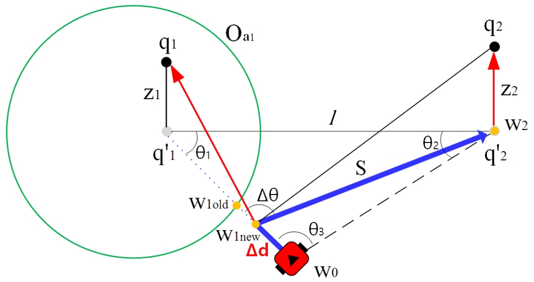

Figure 4: Finding the optimal deployment location w_{1new} for two given tasks, q_1 and q_2 in 3D space.

as follows:

$$\frac{\xi - \Delta d}{v_R} = mv(\mathbf{w}_{1new}, \mathbf{w}_2) + \tau \tag{3}$$

where $\xi = \|\overline{\mathbf{w}_0 q'_1}\|$, $mv(\mathbf{w}_{1new}, \mathbf{w}_2)$ is the duration of CR's moving time from $\mathbf{w}_{1new}$ to $\mathbf{w}_2$, and:

$$S = \sqrt{l^2 + (\xi - \Delta d)^2 - 2l(\xi - \Delta d)\cos\theta_1} \tag{4}$$

$$rt(\theta_{C_{\mathbf{w}_{1new}}}) = \left(\theta_3 + \frac{\Delta d}{\xi} \cdot \theta_2\right) / w_C \tag{5}$$

where $rt(\theta_{C_{\mathbf{w}_{1new}}})$ is the function that returns the duration of rotating time at the deployment location $\mathbf{w}_{1new}$.

Expanding on this idea, we can find Δd for q_1 and q_2 by equalizing the durations that first UAV moves from w_{1new} to q_1, and the CR moves from w_{1new} to w_2 plus second UAV moves from w_2 to q_2 as follows:

$$\frac{\sqrt{(\xi - \Delta d)^2 + |z_1|^2}}{v_R} = mv(\mathbf{w}_{1new}, \mathbf{w}_2) + \tau + \frac{|z_2|}{v_R} \tag{6}$$

where $0 \le \Delta d \le \xi$.

3.2 Clustering of Tasks

To find efficient deployment points, we iteratively divide the set of all the tasks into several subsets, which is refered here as *cluster*. In 2D space, we find minimum bounded circle for each cluster so that the center and radius of the circle can be found. Therefore, here we find minimum bounded sphere for each cluster of tasks as follows:

$$\begin{aligned} &\text{minimize} \quad r \\ &\text{subject to} \quad \|q_i - e\| \le r \end{aligned} \tag{7}$$

To solve (7), we first find convex hull (Graham, 1972) so that only outer points are considered for finding the sphere. For α-th cluster of tasks p_α, the center of the bounded sphere (x_α, y_α) and its radius r_α is computed by finding three points (x_1, y_1), (x_2, y_2), (x_3, y_3) which satisfy as follows:

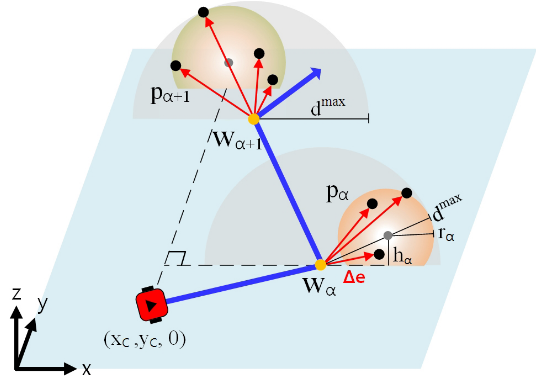

Figure 5: Calculation of deployment locations. The locations are calculated by using the maximum traveling distance of the UAV, the size of the cluster, and the direction to the next cluster.

$$(x_1 - x_\alpha)^2 + (y_1 - y_\alpha)^2 = r_\alpha^2 \tag{8}$$

$$(x_2 - x_\alpha)^2 + (y_2 - y_\alpha)^2 = r_\alpha^2 \tag{9}$$

$$(x_3 - x_\alpha)^2 + (y_3 - y_\alpha)^2 = r_\alpha^2 \tag{10}$$

If any r_α for a cluster is bigger than d^{max}, then the cluster should be divided until all radii of clusters are less than or equal to d^{max} so that the UAVs deployed at a deployment location can reach all task locations in the relevant cluster.

3.3 Determining Deployment Locations

Once a set of clusters is arranged, a series of deployment locations should be calculated. In the previous sub-chapter, we addressed the optimal deployment for two tasks. However, as the number of clusters increases, the UAVs which are deployed in the former deployment location have enough time to fly. Therefore, to reduce the overall time, the CR should deploy UAVs at their maximum traveling distance d^{max} unless the next cluster is the last.

Figure 5 describes this concept. Let there be two clusters of tasks, p_α and $p_{\alpha+1}$ as depicted in Figure 5. Then the CR should stop near by p_α first, then go to $p_{\alpha+1}$. Let the center of p_α, $p_{\alpha+1}$, and the location of the CR be $(x_\alpha, y_\alpha, h_\alpha)$, $(x_{\alpha+1}, y_{\alpha+1}, h_{\alpha+1})$, and $(x_C, y_C, 0)$ respectively. First, we find a line segment between the CR and $(x_{\alpha+1}, y_{\alpha+1}, 0)$ which is the projected point of $(x_{\alpha+1}, y_{\alpha+1}, h_{\alpha+1})$ as follows:

$$y = \frac{y_{\alpha+1} - y_C}{x_{\alpha+1} - x_C}(x - x_C) + y_C \tag{11}$$

where $min(x_C, x_{\alpha+1}) \le x \le max(x_C, x_{\alpha+1})$. Next, we find an another line segment which is perpendicular to (10) and crosses $(x_\alpha, y_\alpha, 0)$ as follows:

$$y = \frac{x_C - x_{\alpha+1}}{y_{\alpha+1} - y_C}(x - x_\alpha) + y_\alpha \quad (12)$$

Then, the deployment location $\mathbf{w}_\alpha$ can be found as a dot on (12). To minimize the travel distance of the CR, we find Δe which satisfies the following equation:

$$(\Delta e)^2 + h_\alpha^2 = (d^{max} - r_\alpha)^2 \quad (13)$$

so that the distance from $\mathbf{w}_\alpha$ to the farthest point in p_α is the same as the maximum traveling distance of the UAV, d^{max}. If a diameter of a cluster is longer than d^{max}, Δe in (13) cannot be solved because $h_\alpha > (d^{max} - r_\alpha)$. Therefore, the deployment point also cannot be acquired.

4 SIMULATION

4.1 Simulation Environment

The goal of this work is to validate the proposed algorithm in 3D space. We implemented the method in Matlab for the simulation. The simulated environment is listed in Table 1. The simulation program is executed on a computer with dual-core 2.90GHz Intel Core i5-5287U CPU, 8GB RAM, and Windows 8.1 64bit operating system. Note that the program code is not fully optimized.

Table 1: The specification of the simulation computer

Processor	Intel Core i5-5287U 2.90GHz
Memory	8GB DDR3
OS	Windows 8.1 (64bit)

4.2 Result

First, the deployment for two tasks is examined. The result is shown in Figure 6. First, the CR is located in its initial location in Figure 6(a). In Figure 6(b), the CR approaches to first deployment location w_1. As the CR arrives at w_1, the first UAV is deployed and it begins to fly in Figure 6(c). After finishing all deployment, two UAVs approach their assigned locations in Figure 6(d). Finally, two UAVs arrive the locations simultaneously. From this simulation, we verify the optimality of the proposed deployement method for arbitrary two tasks.

The example of more complex scenario for deployment is given in Figure 7. The spheres imply the maximum traveling distance of the UAV from each deployment location. Task locations are $(57,11,4), (76,59,5), (17,37,6), (13,75,7), (9,26,5), (50,70,3)$. $v_C^{max} = 15.0m/s, w_C = 3.0rad/s, a_C = 10.0m/s^2, \tau = 4.0s, v_R = 1.0m/s$, and d^{max} varies from $7.0m$ to $35.0m$. Figure 7(a) shows the deployment result when $d^{max} = 7.0m$. According to d^{max}, six tasks are separated into six clusters. The CR travels $201.24m$, and it takes 52.95s for all the UAVs reach task locations. Next, the maximum traveling distance increases to $15.0m$ in Figure 7(b). As a result, two tasks with respect to $\mathbf{w}_3$ and $\mathbf{w}_4$ in Figure 7(a) are merged into one cluster. In addition, both the travel distance of the CR and the total duration of time for deployment decreases. Figure 7(c) shows the result when $d^{max} = 25.0m$. In the same manner, both the distance of the CR and the total duration also decreases, and another two tasks are merged into one cluster. By using the proposed method, the efficient path generation for deployment is shown.

5 CONCLUSIONS

In this paper we proposed the UAV deployment algorithm which is efficient and overcomes energy constraint of UAVs. By considering geographical adjacency of multiple tasks, the tasks are divided into several clusters, and then the deployment location for each cluster is determined by the proposed algorithm. The deployment location is calculated by considering the dynamics of CR and UAVs and energy constraint of UAV to minimize the duration of time that all UAVs are reached their given locations. Since the previously proposed algorithm was applicable only in 2D space, we extended it to 3D space and dealt with the problems that arose from the dimension. We have implemented the proposed method in simulation and showed that the method is feasible and efficient. This kind of cooperative deployment strategy can be used for the operations such as drone delivery and planetary exploration.

For future work, we consider belows:

1) Adopting a conventional obstacle avoidance algorithm;
2) Expanding the method to UAV collection problem;
3) Conducting experiments in real robot platforms;

ACKNOWLEDGEMENTS

This work was supported in part by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIP) (No.2013R1A2A1A05005547), in part by the Brain

Korea 21 Plus Project, in part by ASRI, and in part by Samsung Electro-Mechanics Co., Ltd.

REFERENCES

Caballero, F., Merino, L., Ferruz, J., and Ollero, A. (2009). Vision-based odometry and slam for medium and high altitude flying uavs. *Journal of Intelligent and Robotic Systems*, 54(1-3):137–161.

Doherty, P. and Rudol, P. (2007). A uav search and rescue scenario with human body detection and geolocalization. In *AI 2007: Advances in Artificial Intelligence*, pages 1–13. Springer.

Graham, R. L. (1972). An efficient algorith for determining the convex hull of a finite planar set. *Information processing letters*, 1(4):132–133.

Lee, H., Jeon, J., and Lee, B. (2015a). An efficient cooperative deployment of robots for multiple tasks. In *Robotics and Automation (ICRA), 2015 IEEE International Conference on*, pages 5419–5425. IEEE.

Lee, H., Yoo, H., and Lee, B. (2015b). Deployment method of uavs with energy constraint for multiple tasks. *Electronics Letters*, 51(21):1650–1652.

Luotsinen, L. J., Gonzalez, A. J., and Boeloeni, L. (2004). Collaborative uav exploration of hostile environments. Technical report, DTIC Document.

Mei, Y., Lu, Y.-H., Hu, Y. C., and Lee, C. G. (2006). Deployment of mobile robots with energy and timing constraints. *Robotics, IEEE Transactions on*, 22(3):507–522.

Parker, L. E. (2008). Distributed intelligence: Overview of the field and its application in multi-robot systems. *Journal of Physical Agents*, 2(1):5–14.

Pei, Y. and Mutka, M. W. (2012). Steiner traveler: Relay deployment for remote sensing in heterogeneous multi-robot exploration. In *Robotics and Automation (ICRA), IEEE International Conference on*, pages 1551–1556.

Ryan, A. and Hedrick, J. K. (2005). A mode-switching path planner for uav-assisted search and rescue. In *Decision and Control, 2005 and 2005 European Control Conference. CDC-ECC'05. 44th IEEE Conference on*, pages 1471–1476. IEEE.

Rybski, P. E., Papanikolopoulos, N. P., Stoeter, S., Krantz, D. G., Yesin, K. B., Gini, M., Voyles, R., Hougen, D. F., Nelson, B., Erickson, M. D., et al. (2000). Enlisting rangers and scouts for reconnaissance and surveillance. *Robotics & Automation Magazine, IEEE*, 7(4):14–24.

Saska, M., Krajník, T., and Pfeucil, L. (2012). Cooperative μuav-ugv autonomous indoor surveillance. In *Systems, Signals and Devices (SSD), 9th International Multi-Conference on*, pages 1–6.

Semsch, E., Jakob, M., Pavlíček, D., and Pěchouček, M. (2009). Autonomous uav surveillance in complex urban environments. In *Web Intelligence and Intelligent Agent Technologies, 2009. WI-IAT'09. IEEE/WIC/ACM International Joint Conferences on*, volume 2, pages 82–85. IET.

Sujit, P. and Beard, R. (2008). Multiple uav exploration of an unknown region. *Annals of Mathematics and Artificial Intelligence*, 52(2-4):335–366.

Sujit, P., Sousa, J., and Pereira, F. L. (2009). Uav and auvs coordination for ocean exploration. In *Oceans 2009-Europe*, pages 1–7. IEEE.

Wang, J., Smith, C., Staskevich, G., and Abbe, B. (2015). A distributed deployment algorithm for mobile robotic agents with limited sensing/communication ranges. In *Electro/Information Technology (EIT), IEEE International Conference on*, pages 530–535.

Yan, Z., Jouandeau, N., and Cherif, A. A. (2013). A survey and analysis of multi-robot coordination. *International Journal of Advanced Robotic Systems*, 10.

Yang, Y., Minai, A., and Polycarpou, M. M. (2005). Evidential map-building approaches for multi-uav cooperative search. In *Proceedings of the American Control Conference*, volume 1, page 116.

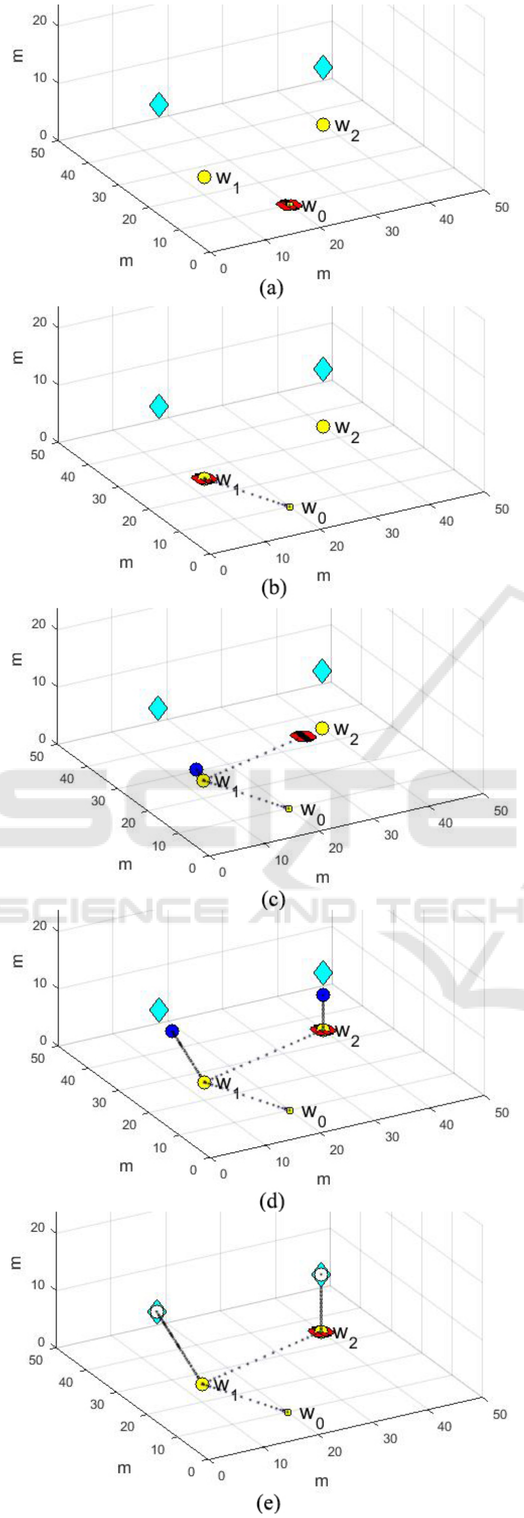

Figure 6: Deployment procedure. (a) Initial state (b) The CR approaches to w_1 (c) The CR approaches to w_2, and first UAV moves to first task location (d) Two UAVs are approaching (e) All UAVs reach their assigned locations.

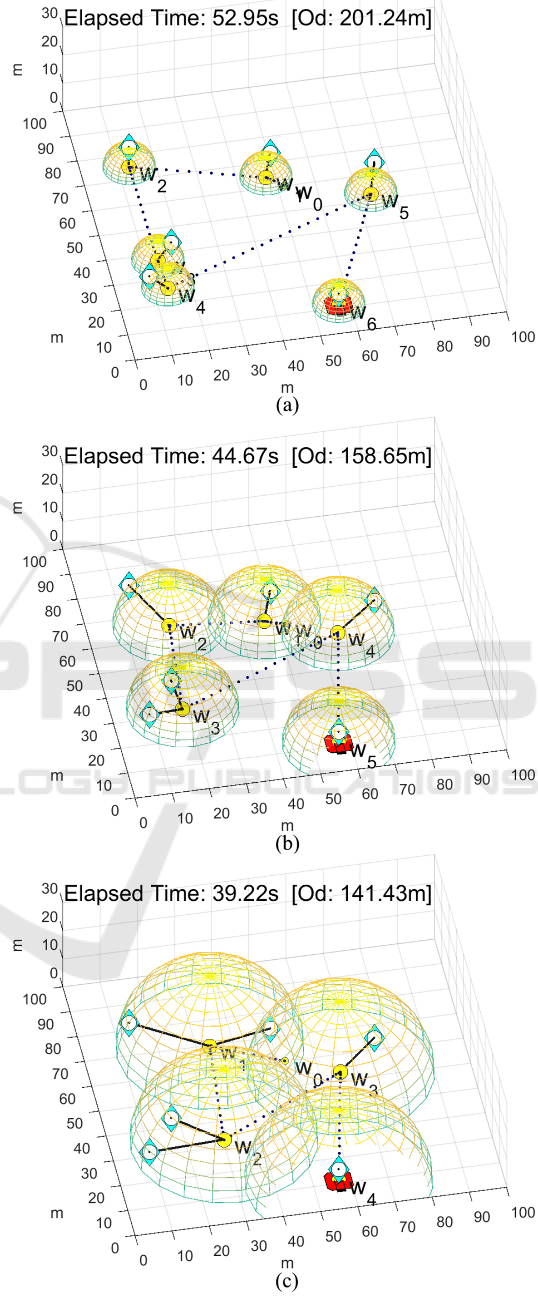

Figure 7: Deployment Example for six tasks in $(100m \times 100m \times 30m)$. We set $v_C^{max} = 15.0m/s, w_C = 3.0rad/s, a_C = 10.0m/s^2, \tau = 4.0s$, and $v_R = 1.0m/s$. (a) $d^{max} = 7.0m$ (b) $d^{max} = 15.0m$ (c) $d^{max} = 25.0m$ (d) $d^{max} = 35.0m$.