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ORIGINAL ARTICLE

Bargaining Model-Based Coverage Area Subdivision of Multiple UAVs in Remote Sensing

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Abstract

Purpose Unmanned aerial vehicles (UAVs) have recently been used for remote sensing because they can fly from low to relatively high altitudes along a planned route and obtain the corresponding resolutions. In remote sensing, the limitations of a single UAV become more apparent as the size of the exploration area increases. In such situations, a multi-UAV setup is required, along with appropriate task allocation and area subdivision.
Methods In this study, we propose area segmentation based on Rubinstein's bargaining model for subdivision of coverage area among multiple UAVs for remote sensing.
Results The negotiation between the two agents and the division of the territory among the three agents according to the field of view (FOV) of the UAVs were elucidated; the experiments were conducted with satellite images obtained from Google Maps.
Conclusions For remote sensing using multiple UAVs, we proposed an area segmentation method using weak cooperation. The segmentation was based on the Rubinsteind route and obtain the correspondiended to two as well as three agents.

Keywords Area subdivision · Multi-robot system · Negotiation · Rubinsteinplebargaining model · Task allocation · Unmanned aerial vehicle

Introduction

Remote sensing primarily employs aerial images obtained using satellites, aircraft, etc. Aerial images obtained using satellites and aircraft are of relatively low resolutions; moreover, the frequency of observation and image use is low, which makes it difficult to obtain more accurate information. In addition, when the area of exploration is small, the use of satellites and aircraft is not cost-effective, which ultimately results in low-resolution images being obtained. Unmanned aerial vehicles (UAVs) can fly from low to relatively high altitudes along a planned route and obtain the corresponding resolutions. Thus, UAVs are more efficient in terms of both cost and resolution when compared with satellites and aircraft; as such, they are used significantly in remote sensing (Niethammer et al. 2012; Matese et al. 2012; Kim et al. 2019).

The area that a single UAV can handle is limited by its battery capacity; the size of the area is also limited by the time required to process it. Therefore, as the size of an exploration area increases, the limitations of a single UAV become more pronounced, and its efficiency decreases. Thus, an expansion to a multi-UAV setup is required. Multi-robot systems (MRS) present considerable advantages over single robot systems. These advantages include the ability to resolve more complex tasks, superior system reliability, and enhanced system performance (Parker et al. 2016; Ju and Son 2018; Ju and Son 2019a; Ju and Son 2019b; Kim and Son 2020). For these reasons, the need to utilize multiple UAV systems is increasing, and many studies are currently underway to fulfill this objective. Tasks that are difficult to perform using a single UAV can be performed using multiple UAVs; these tasks can also be efficiently performed via collaboration within their workspace. However, as the number of UAVs increases, it becomes increasingly difficult to handle the control complexity and ensure stability in an uncertain environment. It is also difficult to cope with unpredictable errors or accidents such as collision between UAVs (Ju and Son 2019a). Moreover, in the case of remote operation of a multi-robot, information on the global status of the multi-robot system is required to

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personalize situation awareness of the remote environment. However, as the number of remote robots increases, the cognitive load required to synthesize the global state also increases rapidly (Hong et al. 2017).

Multi-robot cooperation can be roughly divided into two classes: strong and weak cooperation. Strong cooperation (Kalra et al. 2005) implies the cooperation of two or more robots to complete a task, such as lifting a large object that cannot be lifted by a single robot. These robots need to continuously coordinate with respect to their positions and statuses. Weak cooperation (Ma et al. 2006) indicates that a task can be divided into sub-tasks, each of which can be performed by a single robot. Weak cooperation requires initial coordination when the division of tasks is being planned.

In the case of remote sensing, the exploration of a designated area can be performed by one robot. However, a multi-robot system is effective because the time required to explore a given area would increase according to the size of the exploration area if only a one robot was used. The exploration of a large area can be performed by a team of robots. The entire area can be divided into sub-areas, with each sub-area being assigned to a single robot, which does not require continuous communication. Therefore, in the case of weak cooperation, remote sensing can be performed using multi-robots.

For area division, partitioning algorithms and strategies can be used to distribute known or unknown areas (Balampanis et al. 2017). Using the Voronoi diagram, areas are designated via creation of partitions enabling safe and uniform distribution of a number of robots (Alitappeh and Pimenta 2016). By means of a sweep-line approach along with a zigzag pattern, a sub-area is assigned to the robot that is most appropriate in terms of its relative capability (Maza and Ollero 2007). Proper area segmentation algorithms need to be provided for robot teams with respect to the initial positions of the robots (Kapoutsis et al. 2017).

Negotiation algorithms are also used in this cooperation. Negotiations have been widely investigated in the context of socioeconomic studies employing game theory, among other methods. Game theory has been investigated and applied to help determine how a balanced choice is made. Examples include Action-Based Fictitious Play (Brown 1951), Utility-Based Fictitious Play (Fudenberg et al. 1998; Fudenberg and Levine 1995), and Regret Matching (Hart and Mas-Colell 2000). Research is also being conducted using negotiation strategies to allocate work in multi-robot systems. Task allocation for multiple robots employs a game theory-based negotiation approach (Cui et al. 2013). In addition, game theory can be used to analyze the physical interaction behavior of both humans and robots (Li et al. 2016). Task allocation employing relevant competition and collaboration algorithms, is described in (Garapati et al. (2017).

In this study, we propose a negotiation method to distribute the workspace of each UAV based on Rubinstein's bargaining model (Rubinstein 1982), one of the several game theories employed in the context of remote sensing using multiple UAVs.

Multi-UAV Task Allocation and Area Subdivision

Multi-UAV Remote Sensing

The effectiveness of exploration depends on the accuracy of the coverage of the area and how the time taken to explore the area. In the case of UAV remote sensing, usage of multiple UAVs may not always be effective. Appropriate numbers of robots should be used depending on the size of the exploration area. When multiple UAVs are used, they may not be effective, as collisions between UAVs can occur owing to overlapping path and operation conditions. As such, multiple robots are not required when exploring small areas. However, when the area becomes larger, more UAVs are required, which enables the task to be performed more efficiently. The most effective way to perform the exploration task is to allocate a specific area to each UAV. The entire area is divided, and a sub-area is assigned to each UAV, so that the workspaces do not overlap. Each UAV collects information about its assigned

Fig. 1 Example with three UAVs, showing each UAV with its allocated sub-area

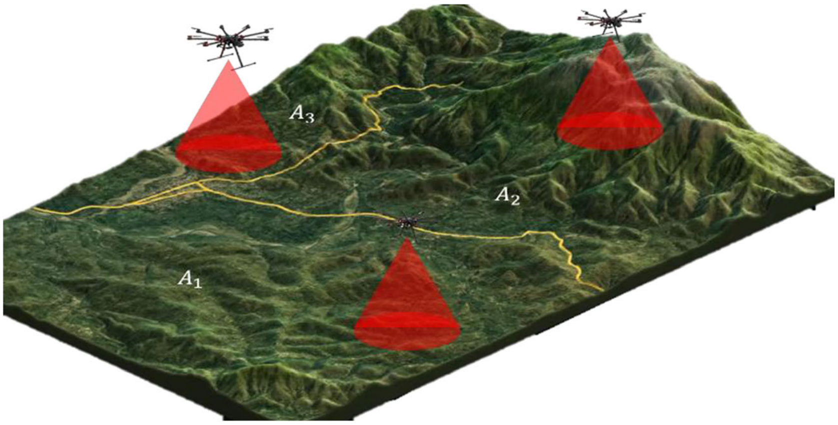

Table 1 Bargaining model algorithm

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Algorithm 1 bargaining model algorithm
Input: discount factor $\delta_1$, $\delta_2$, price ($p$)
Output: $p_1$, $p_2$ dividing into two agents
  offer to other agent
  while accept do
    if accept then
      negotiation terminate
    else
      Round $i$ ← Round $i + 1$
      counteroffer
    end if
  end while
```

area, following which the collected information from all UAVs is combined to obtain information about the entire area.

The centralized control system is used to allocate a workspace to each UAV. The task assigned to each UAV is performed only in the assigned area, and areas assigned to other UAVs are not explored. However, real-world implementation, overlap may inevitably occur owing to rotation according to path planning or path tracking errors due to external forces. Fig. 1 shows an example of an area partitioned among three UAVs. In Fig. 1, A1, A2, and A3 denote the sub-area of the total area, and remote sensing is performed in the sub-areas. It is necessary to consider potential conflicts between the different UAVs, when exploring aspects such as flight altitude difference and path planning.

Task Negotiation

The exploration of the entire considered area is subject to the negotiation process depending on the number of robots. The purpose of the negotiation process is to appropriately divide the exploration area into sub-areas and assign each sub-area to the robots for exploration. In area segmentation negotiations, the sub-areas are determined on the basis of the number of robots considered to perform the task. Each agent wants to be allocated to the largest possible area and also offers itself the largest share and reduces the value until the other party accepts. Though negotiation, each agent can maximize the area allocated. Task allocation is performed with respect to each agent for the subdivided area.

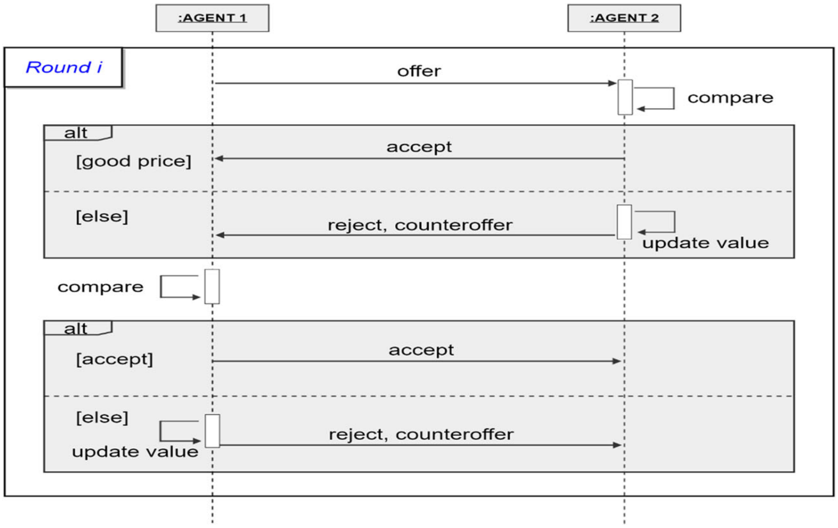

Fig. 2 Negotiation steps for the case of two agents

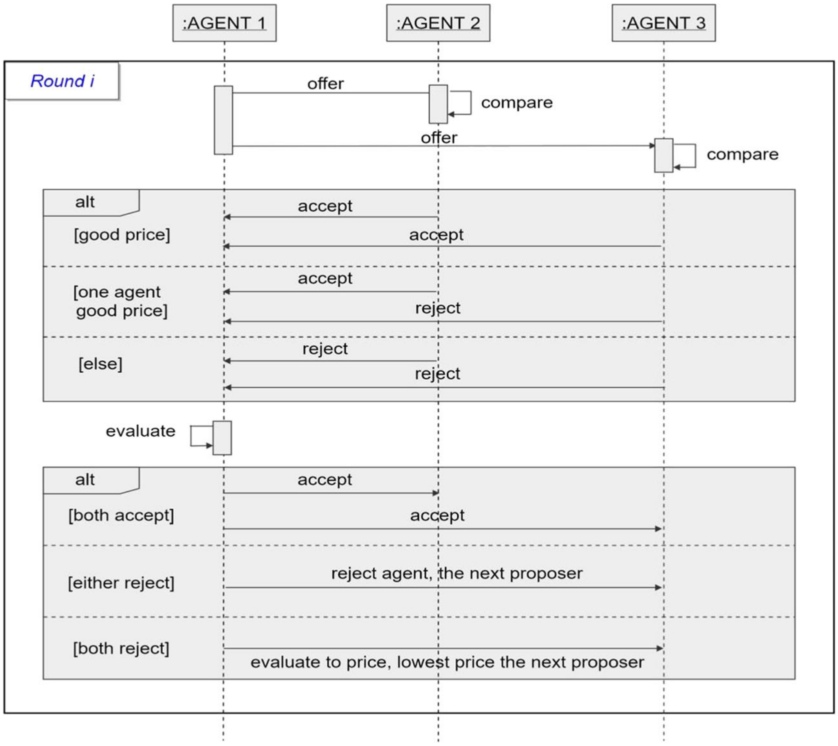

Fig. 3 Negotiation steps for the case of three agents

Rubinstein's Bargaining Model

The Rubinstein's bargaining game is a model in which two players decide how a pie of size 1 should be divided. A bargaining game essentially requires the two players to have complete information about each other. One player proposes the division of the pie over an infinite time horizon for both players, which the other player can accept or reject. If the other player agrees, negotiations complete in round, and both players agree in the first period. If the other player rejects the proposal, the competitive equilibrium prevails in the first period and the second round of negotiation begins in the form of a counteroffer; this process is not performed as a one-sided offer by a single agent (Caparrós 2016). The bargaining model algorithm is described in Table 1.

In the case of two agents (UAVs), each agent suggests the

Table 2 Extended bargaining model algorithm

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Algorithm 2 Extended bargaining model algorithm
Input: discount factor $\delta_1$, $\delta_2$, $\delta_3$, price ($p$)
Output: $p_1$, $p_2$, $p_3$ dividing into three agents
  offer to other agent
  while accept do
    if accept then
      negotiation terminated
    else if either reject then
      reject agent ← proposer
      Round $i$ ← Round $i + 1$
    else if both reject then
      lowest price agent ← proposer
      Round $i$ ← Round $i + 1$
    end if
  end while
```

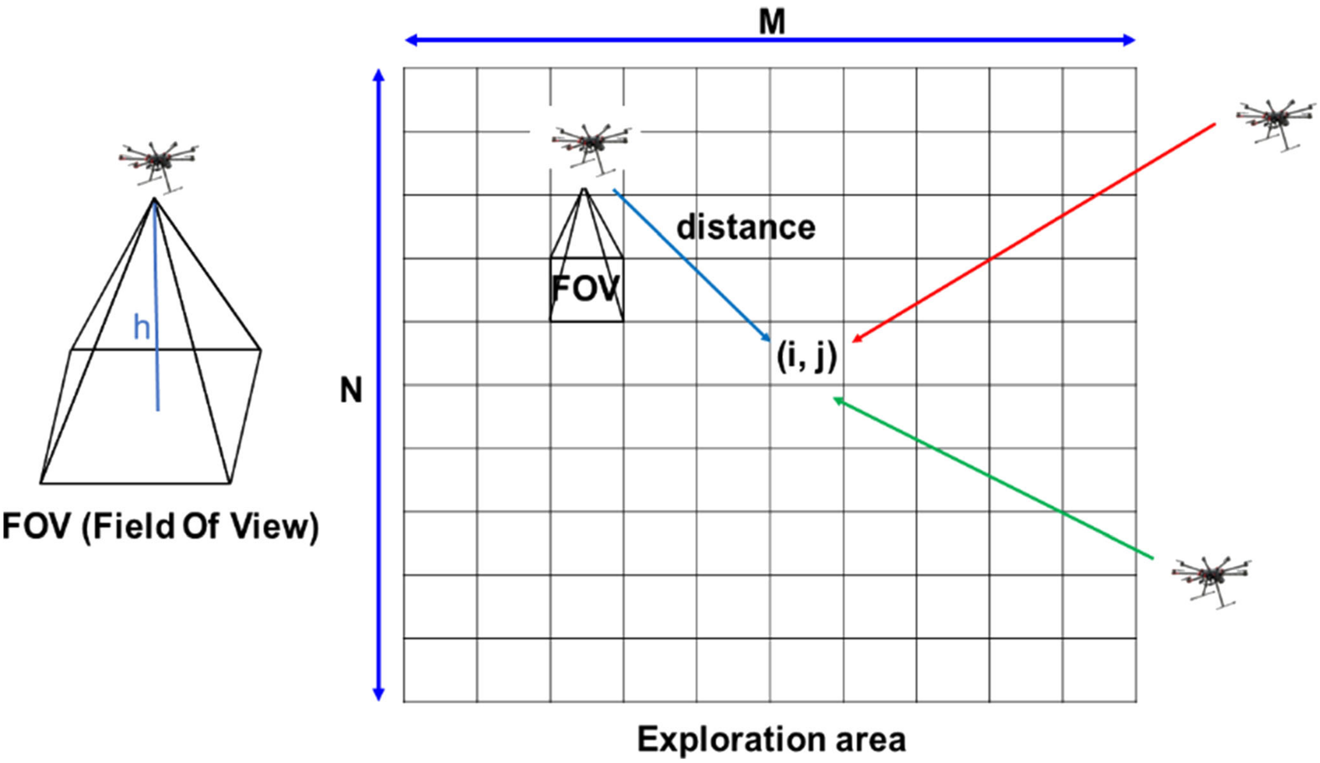


Fig. 4 Exploration area is segmented according to the FOV ($N \times M$). The grid size depends on the FOV

amount that they want. Fig. 2 shows the negotiation protocol. One agent proposes a price, and the other agent compares the price and proceeds in round i to decide whether to accept or reject the proposal. If the proposal is accepted, negotiation is terminated; if the proposal is rejected, the proceeds to round i + 1. Specifically, if the first agent suggests a value of p, the respondents would be left with 1-p. The respondents decide whether or not to accept based on 1-p values. If they refuse, a counteroffer is made. At this time, a discount factor (δ) signifies that a negotiation cost is applied while the value is proposed to prevent duplication of values. The discount factors are determined by the player's capacity, and these discount factors are $0 < \delta_1 < 1$ and $0 < \delta_2 < 1$, $p_{i+1} = p_i \cdot \delta$ ($i = 1, \cdots, n$). As the negotiation progresses, the agent reaches an equilibrium point. The final p is defined as in Eq. (1).

$$p(\delta_1, \delta_2) = \frac{1-\delta_2}{1-\delta_1\delta_2}, \tag{1}$$

where δ is discount factor, p is price.

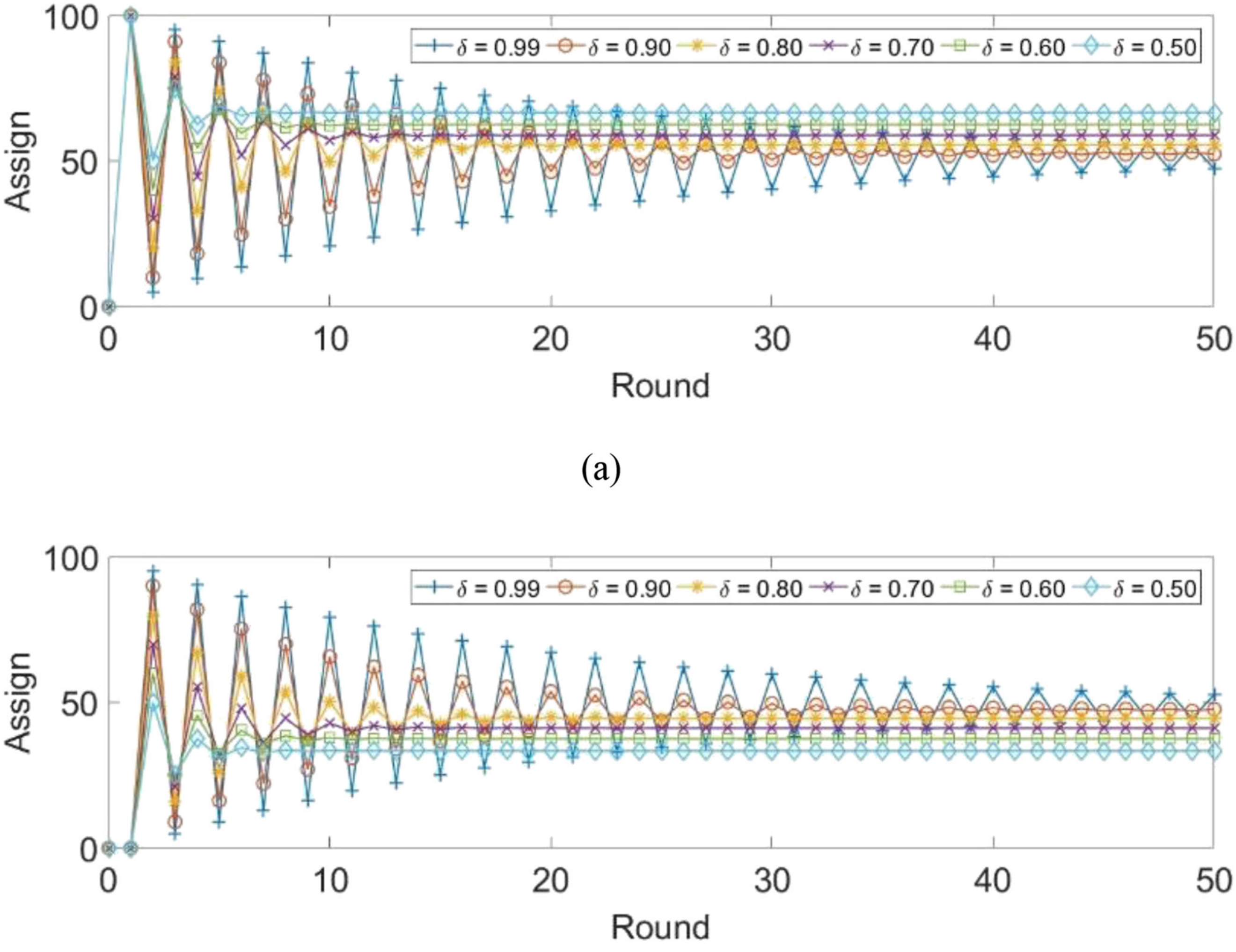
Extended Rubinstein's Bargaining Model

In the case of more than two agents (UAVs), negotiation can be extended; however, the solution in the cases of three or more agents is complicated. Therefore, such cases must also be considered. If the number of agents exceeds three, the solution does not change significantly from that in cases with three agents. Therefore, we focus on the case of three agents.

In the case of three agents (UAVs), the order in which each agent makes a proposal increases in importance, unlike the case in which there are two agents. Fig. 3 shows the negotiation protocol. In the first negotiation round, the order of proposals is not as important as that in the subsequent negotiation process. In the first negotiation round, a share is offered to two other agents, considering the proposing agent's own share. The other two agents accept the proposal if their assigned shares appear acceptable; otherwise, they reject the offer. At this time, it is assumed that all parties know how to distribute the given quota. For the next negotiation round, in which a subsequent proposal is made, the agent receiving the lowest share among those who refused the previous offer begins the new offer. The extended bargaining model algorithm is described in Table 2.

Coverage Area Subdivision

Prior to the area division, the area must be defined. First, information about the exploration area is obtained from the satellite, and the entire area field of exploration is divided into images as obtained by the UAV at a specific height. The workspace comprises a grid environment, as shown in Fig. 4. The grid size depends on the field of view (FOV) of the UAV; the UAV is assumed to fly at a constant height. For environments divided on the basis of the FOV of the UAV, negotiations are conducted to determine the sub-area to be allocated to each UAV. Each UAV negotiates with the



(a)

(b)

Fig. 5 Case a: two agents, result on the basis of round and discount factor for each agent. **a** Agent 1. **b** Agent 2

objective of obtaining the largest possible area. At this time, negotiation is performed considering a discount factor and the distance between the initial location of the UAV and the location of the grid cell. Therefore, the area allocated through negotiation is affected by the initial location of each UAV. Upon weighting of the distances from the grid cell (i, j), each UAV can be assigned the areas closest from the initial position. However, in this study, the initial positions of the UAVs are all assumed to lie on the same line. $p(\delta)$ can be defined as in Eq. (2)

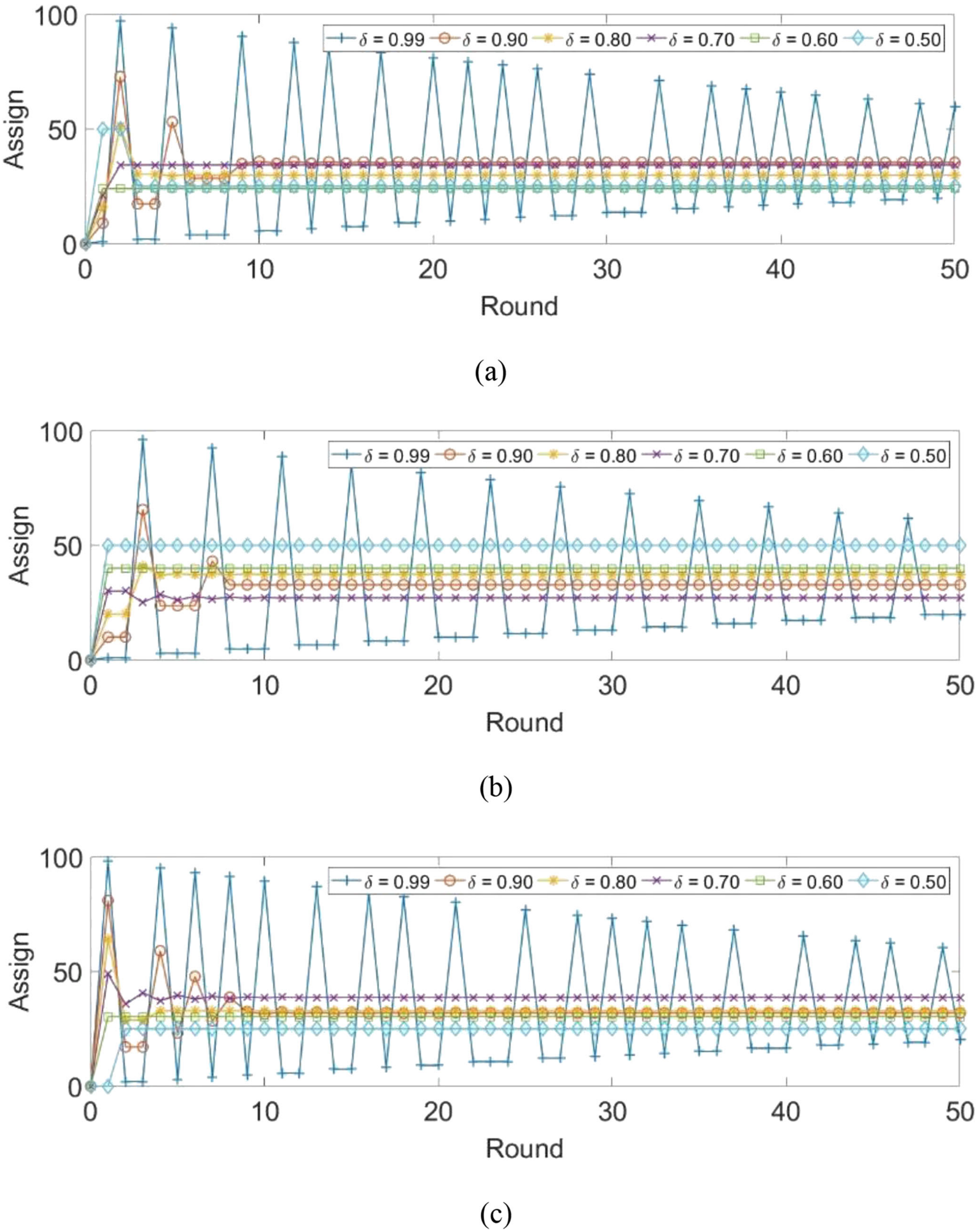
$$p(\delta) = W_k \cdot \delta_k, \quad 0 < W_k < 1, \quad W_k = d_{ij}^k, \tag{2}$$

where W_k is weight of the distance from the UAV location and d_{ij}^k is the distance from the UAV to cell i, j.

Experimental Results

Actual UAVs were not used, and the proposed area subdivision method was tested only through numerical simulations. In this simulation, the robots reduced the assigned areas in each round consecutive negotiation round as required on the basis of the discount factor. In the case of a small discount factor, uneven negotiations result in uneven allocation. Therefore, in this experiment, discount factors of 0.98 and 0.96 were adopted to examine the rounds in which negotiations were completed with relatively uniform distribution. For example, a discount factor of 0.96 implies that the allocated subdivision for the next round would be 4% smaller.

If the discount rate is too low, the assigned area would drop significantly, and the allocation would be uneven, and indicating pointless negotiation. This may decrease the



(a)

(b)

(c)

Fig. 6 Case b: three agents, result on the basis of round and discount factor for each agent. **a** Agent 1. **b** Agent 2. **c** Agent 3

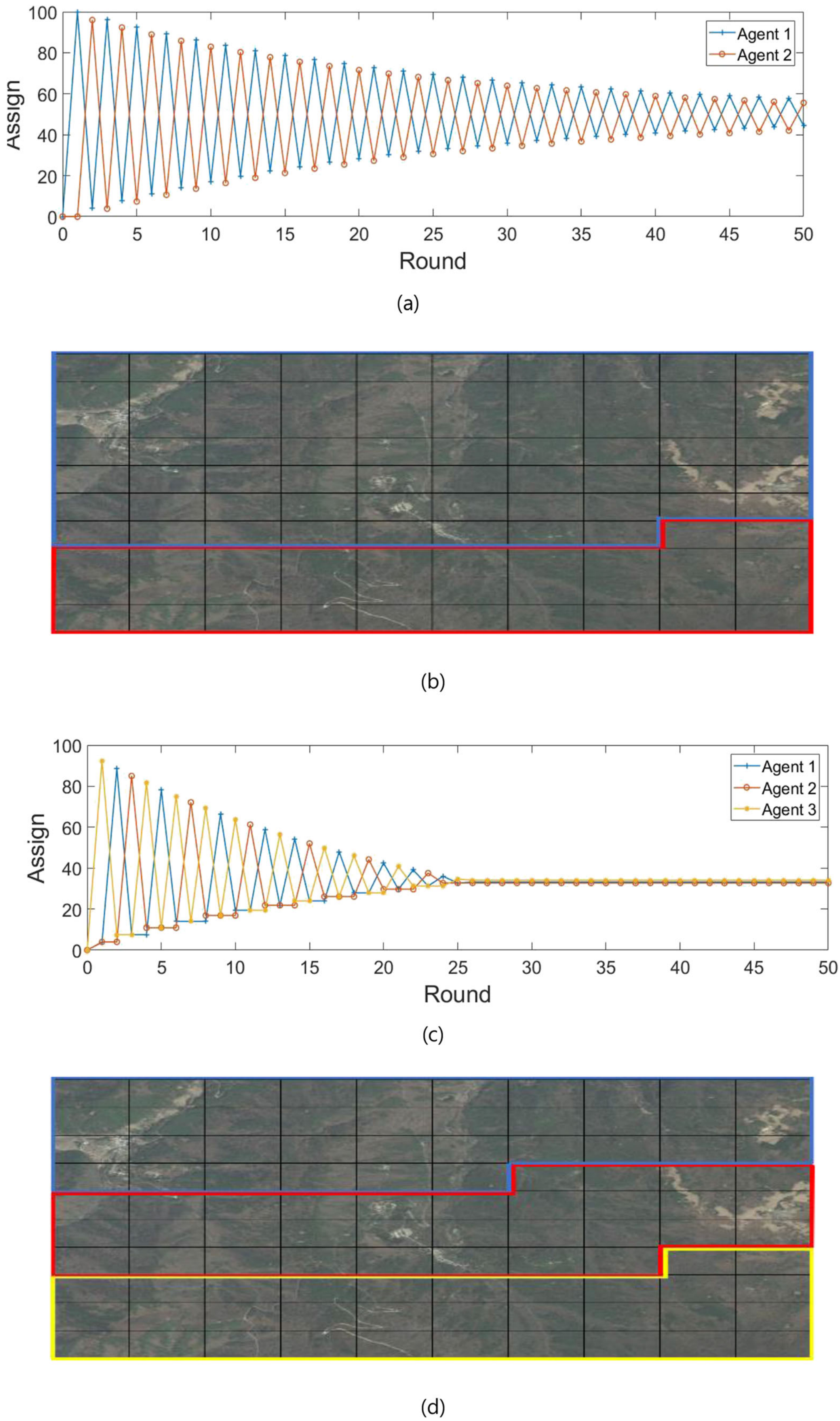
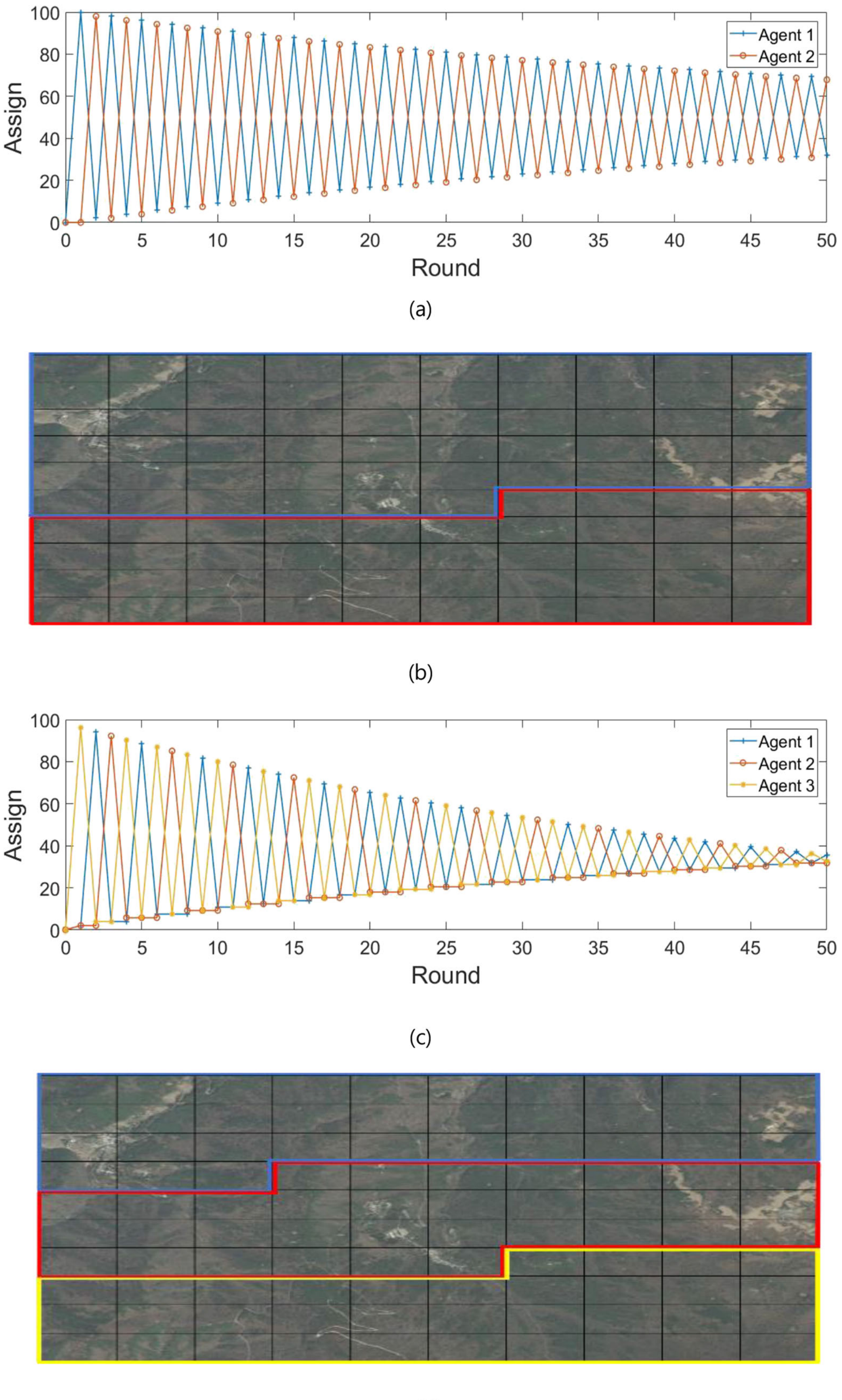


Fig. 7 Area subdivision according to discount factor = 0.96, round 50. **a** Negotiation result for two agents. **b** Area subdivision result for two agents. **c** Negotiation result for three agents. **d** Area subdivision result for three agents



(a)

(b)

(c)

(d)

Fig. 8 Area subdivision according to discount factor = 0.98, round 50. **a** Negotiation result for two agents. **b** Area subdivision result for two agents. **c** Negotiation result for three agents. **d** Area subdivision result for three agents efficiency of the performed tasks. The distribution can be performed non-uniformly in absolute quantities according to the state of the UAVs. However, UAVs under more efficient operating conditions than those of other UAVs require a large area, so the uneven distribution of this absolute amount can be considered uniform.

Figs. 5 and 6 show negotiation results on the basis of round and discount factor for each agent. Fig. 5 shows the results for two agents, (a) shows the results for agent 1, and (b) shows the results for agent 2. Fig. 6 shows the results for three agents, (a) shows the result for agent 1, (b) shows the result agent 2, and (c) shows the result agent 3. The end of the negotiation round is indicated by use of the discount factor and change in the assigned value for each agent. In the process of applying the discount factor to proceed with the next round of negotiation, the smaller is the discount factor value, the greater is the decrease in value as the negotiation proceeds. The reduced value owing to the cost of negotiation to enter the next round is lesser than the value proposed. Therefore, the smaller is the value of the discount factor, the lesser are the negotiation rounds required; there exists both a balance and difference in each value. The larger is the value of the discount factor, the more even is the distribution made, and the more are the negotiation rounds required.

Figs. 7 and 8 show the negotiation results on the basis of round and discount factor, as well as the results of the area subdivision. Fig. 7 shows the result obtained on a using discount factor of 0.96 at the 50th negotiation round, where (a) shows the result for two agents, and (b) shows the result of area subdivision according to the negotiation shown in (a). Fig. 7 (c) shows the result for three agents, and (d) shows the result of area subdivision according to the negotiation shown in (c). Fig. 8 shows the result obtained on using a discount factor of 0.98 at the 50th negotiation round, where (a) shows the result for two agents, and (b) shows the result of area subdivision according to the negotiation shown in (a). Fig. 8 (c) shows the result for three agents, and (d) shows the result of area subdivision according to the negotiation shown in (c). The same discount factor and number of rounds were applied for the area segmentation, and the area was divided according to the order of the agents without considering the initial position of the UAV. It is assumed that the initial positions of all UAVs are the same.

Discussion

In this paper, we proposed bargaining model-based area segmentation for multiple UAVs for remote sensing. The proposed negotiation strategy can enable the area to be divided more effectively when dealing with multiple UAVs. However, optimization was not achieved owing to UAV state variables not being considered. Therefore, in the future, we need to address the following challenges:

Weighted UAV Condition Area Partition

Hitherto, the proposed negotiation strategy has not considered the initial location and speed of the UAVs and the distance from the initial location to the grid. Optimization was not achieved because the UAV state variables were not sufficiently considered. In addition, the division could be more effectively performed depending on the state of the UAV. The weighted UAV condition area partition $p(\delta_k)$ can be defined as in Eq. (3).

$$p(\delta_k) = W_{loc}^k \cdot W_{fov}^k \cdot W_{vel}^k \cdot W_{bat}^k \cdot W_k \cdot \delta_k \tag{3}$$

where W_{loc}^k is the initial location of the UAV, W_{fov}^k is the FOV of the UAV, W_{vel}^k is the capacity of the UAV, W_k is the distance from the UAV location, and δ_k is the discount factor applied. If the area partitioning is optimized, shorter exploration times and increased work efficiencies can be expected thereupon. Furthermore, if a path plan to minimize overlap were to be established, the best working scenario would consequently be obtained.

Heterogeneous Robot

It is assumed that the statuses of multi-homogeneous robots such as altitude, battery, and velocity are identical. However, heterogeneous robots exist in different states (Badreldin et al. 2013). Therefore, the different states of the robot (e.g., UAV location, FOV, velocity, battery) must be considered. As there will exist differences in the processing capabilities of the UAVs, the type of area partitioning must also be determined accordingly. In addition, for separated areas, path planning for UAVs is necessary and important for ensuring that remote sensing tasks are completed accurately and efficiently. However, the problem of multiple UAVs covering multiple-separated areas is often not considered owing to their complexity (Chen et al. 2019).

Strong Cooperation

We divided the workspace into sub-areas from the perspective of weak cooperation. However, cases such as UAV failure during a task or task failure attributable to a battery problem should be considered. In these cases, continuous communication between UAVs is necessary. If such continuous communication is not possible, it can be assumed that a problem exists within the UAV, and the system can then perform the remaining tasks using alternate UAVs. However, because the loss of communication as result of to distance is not necessarily recognized as a problem, techniques for considering or improving communication across distances are also required.

Conclusions

In this paper, we proposed area division on the basis of Rubinstein's bargaining model for multiple UAVs in the context of remote sensing. The negotiation model was generally employed for negotiations between two agents, and many factors must be considered when three or more agents are involved in negotiations. Therefore, we proposed a method that extended the bargaining model algorithm from two agents to three agents. However, our method is also limited in that it cannot be generalized for more than three agents. In addition, various states such as UAV battery, FOV, and velocity were assumed to be the same, and the area was divided through numerical simulation. The partitioned area was not optimized because the state variables were not sufficiently considered. If such state variables are considered, it is expected that the most optimal UAV area subdivision would be achieved, and the optimal work efficiency would be achieved through path planning for the divided sub-areas.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

References

Alitappeh, R. J., & Pimenta, L. C. (2016). Distributed safe deployment of networked robots. In *Distributed autonomous robotic systems* (pp. 65–77). Tokyo: Springer. https://doi.org/10.1007/978-4-431-55879-8_5.

Badreldin, M., Hussein, A., & Khamis, A. (2013). A comparative study between optimization and market-based approaches to multi-robot task allocation. *Advances in Artificial Intelligence*, 1–11. https://doi.org/10.1155/2013/256524.

Balampanis, F., Maza, I., & Ollero, A. (2017). Coastal areas division and coverage with multiple UAVs for remote sensing. *Sensors, 17*(4), 808. https://doi.org/10.3390/s17040808.

Brown, G. W. (1951). Iterative solution of games by fictitious play. *Activity Analysis of Production and Allocation, 13*(1), 374–376.

Caparrós, A. (2016). Bargaining and international environmental agreements. *Environmental and Resource Economics, 65*(1), 5–31. https://doi.org/10.1007/s10640-016-9999-0.

Chen, J., Du, C., Lu, X., & Chen, K. (2019). Multi-region coverage path planning for heterogeneous unmanned aerial vehicles systems. In: 2019 *IEEE International Conference on Service-Oriented System Engineering (SOSE)*, 356-3565. IEEE. https://doi.org/10.1109/SOSE.2019.00060.

Cui, R., Guo, J., & Gao, B. (2013). Game theory-based negotiation for multiple robots task allocation. *Robotica, 31*(6), 923–934. https://doi.org/10.1017/S0263574713000192.

Fudenberg, D., & Levine, D. (1995). Consistency and cautious fictitious play. *Journal of Economic Dynamics and Control., 19*, 1065–1089. https://doi.org/10.1016/0165-1889(94)00819-4.

Fudenberg, D., Drew, F., Levine, D. K., & Levine, D. K. (1998). *The theory of learning in games* (Vol. 2). MIT press.

Garapati, K., Roldán, J. J., Garzón, M., del Cerro, J., & Barrientos, A. (2017). A game of drones: game theoretic approaches for multi-robot task allocation in security missions. In *Iberian Robotics conference* (pp. 855–866). Cham: Springer. https://doi.org/10.1007/978-3-319-70833-1_69.

Hart, S., & Mas-Colell, A. (2000). A simple adaptive procedure leading to correlated equilibrium. *Econometrica, 68*(5), 1127–1150. https://doi.org/10.1111/1468-0262.00153.

Hong, A., Lee, D. G., Bülthoff, H. H., & Son, H. I. (2017). Multimodal feedback for teleoperation of multiple mobile robots in an outdoor environment. *Journal of Multimodal User Interface, 11*(1), 67–80. https://doi.org/10.1007/s12193-016-0230-y.

Ju, C., & Son, H. I. (2018). Multiple UAV systems for agricultural applications: control, implementation, and evaluation. *Electronics, 7*(9), 162. https://doi.org/10.3390/electronics7090162.

Ju, C., & Son, H. I. (2019a). A distributed swarm control for an agricultural multiple unmanned aerial vehicle system. *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering, 233*(10), 1298–1308. https://doi.org/10.1177/0959651819828460.

Ju, C., & Son, H. I. (2019b). Modeling and control of heterogeneous agricultural field robots based on. *Ramadge of heterogeneouIEEE Robotics and Automation Letters, 5*(1), 48–55. https://doi.org/10.1109/LRA.2019.2941178.

Kalra, N., Ferguson, D., & Stentz, A. (2005). Hoplites: a market-based framework for planned tight coordination in multirobot teams. In *Proceedings of the 2005 IEEE international conference on robotics and automation* (pp. 1170–1177). Spain: Barcelona. https://doi.org/10.1109/ROBOT.2005.1570274.

Kapoutsis, A. C., Chatzichristofis, S. A., & Kosmatopoulos, E. B. (2017). DARP: divide areas algorithm for optimal multi-robot coverage path planning. *Journal of Intelligent & Robotic Systems, 86*(3-4), 663–680. https://doi.org/10.1007/s10846-016-0461-x.

Kim, J., & Son, H. I. (2020). A Voronoi diagram-based workspace partition for weak cooperation of multi-robot system in orchard. *IEEE Access, 8*, 20676–20686. https://doi.org/10.1109/ACCESS.2020.2969449.

Kim, J., Kim, S., Ju, C., & Son, H. I. (2019). Unmanned aerial vehicles in agriculture: a review of perspective of platform, control, and applications. *IEEE Access, 7*, 105100–105115. https://doi.org/10.1109/ACCESS.2019.2932119.

Li, Y., Tee, K. P., Yan, R., Chan, W. L., & Wu, Y. (2016). A framework of humanculture: reas algorithm for optimal multi-robot coverage path pIEEE. *Transactions on Robotics, 32*(6), 1408–1418. https://doi.org/10.1109/TRO.2016.2597322.

Ma, X., Meng, F., Li, Y., Chen, W., & Xi, Y. (2006). Multi-agent-based Auctions for multi-robot exploration. In *2006 6th World Congress on Intelligent Control and Automation* (pp. 9262–9266). China: Dalian. https://doi.org/10.1109/WCICA.2006.1713793.

Matese, A., Toscano, P., Di Gennaro, S. F., Genesio, L., Vaccari, F. P., Primicerio, J., Belli, C., Zaldei, A., Bianconi, R., & Gioli, B. (2012). Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture. *Remote Sensing, 7*(3), 2971–2990. https://doi.org/10.3390/rs70302971.

Maza, I., & Ollero, A. (2007). Multiple UAV cooperative searching operation using polygon area decomposition and efficient coverage algorithms. In *Distributed autonomous robotic systems 6* (pp. 221–230). Tokyo: Springer. https://doi.org/10.1007/978-4-431-35873-2_22.

Niethammer, U., Jamesm, M. R., Rothmund, S., Travelletti, J., & Joswing, M. (2012). UAV-based remote sensing of the Super-Sauze landslide: evaluation and results. *Engineering Geology, 128*, 2–11. https://doi.org/10.1016/j.enggeo.2011.03.012.

Parker, L. E., Rus, D., & Sukhatme, G. S. (2016). Multiple mobile robot systems. In *Springer handbook of robotics* (pp. 1335–1384). https://doi.org/10.1007/978-3-319-32552-1_53.

Rubinstein, A. (1982). Perfect equilibrium in a bargaining model. *Econometrica: Journal of the Econometric Society*, 97–109. https://doi.org/10.2307/1912531.