Finding and Monitoring Number of Living Entities through Unmanned Aerial

Mahdi Abed Salman
Computer Science
University of Babylon
Babylon, Iraq
mahdi.salman@uobabylon.edu.iq

DOI : http://dx.doi.org/10.31642/JoKMC/2018/090203
Received Feb. 15, 2022. Accepted for publication Apr. 4, 2022

Abstract— *The rapid development of Unmanned Aerial Vehicles UAVs technology opens many new application areas. One of these applications is remote monitoring for living entities (Humans or Animals) within a known area for safety and protection purposes. UAVs are programmable to carry missions according to a specified algorithm. Their ability of movements and actions provide solutions with a reasonable cost. However, how a set of UAVs doing a mission behave cooperatively need to be tested and evaluated in a lab with simulation before moving to operation field. In this paper, a model for scanning determined area using a set of cooperative UAVs is developed and tested. The objective is reducing operation time. The set of affecting parameters is examined. The model is simulated using NetLogo agent-based simulation tool. The results of the experiment of a various settings are conducted.*

Keywords— UAV, Drones, Agent-based model, Cooperative agents, Targets searching.

I. INTRODUCTION

Unmanned Aerial Vehicles UAVs (commercially called drones) are small technical devices battery powered designed to fly for durations relative to their size and battery capacity. According to designating objectives, drones may have many types of sensors such as cameras, IR sensor, positioning device that depends on Global Position Systems GPS, and so on. It also can carry small objects from place to place [1]. Drones are types of robots known as Unmanned Air Vehicles UAVs. We used word drone and UAV interchangeably in this article.

Many applications employ UAVs for gathering information or deliver objects. One such application is monitoring a number of living entities in a region of the wide area [2]. A small set of drones scan the region autonomously is preferred over many other techniques such as stationary sensors or cameras or even by employed people. Hence, such technique never imposes any in-field infrastructure [3]. The IT cost at an information sink is also manageable compared with other techniques.

The purpose of monitoring could be live rescue during disasters or targets finding in defense applications. It also could be used for scientific researching when targets are animals under a study or protection, for example, the distribution of these beings in wilds [4].

Although the topic has, many works have done. Most studies aim to develop the capability of UAVs but few focus on cooperation models of UAVs.

The objective of this study is to estimate the number of living entities within a predefined region using a set of UAVs given each one can know the number of entities located within its vision. UAV use available technology (e.g. advanced video processing or Infrared Red lights IR, etc...) to count the number of targets appearing in its vision. Detection process and technology is out of the scope of this study; we deal only with UAV's behavior and computation.

In this paper, we build an agent-based model to scan a predetermined region cooperatively. Different settings of parameters are considered when the proposed model is simulated and tested. The remaining of this paper is organized as follows: An introduction is presented in section one. Section 2 reviews the related works. The solution methodology and proposed model is presented in section 3. Section 4 presents results and discussed them. Finally, the paper is concluded in section five.

II. RELATED WORK

The problem of searching for targets in regions of a wide area is an objective of many research articles. However, some works focus on the technology used for detection and processing data before counting other deals with the behavior of the drones. Below, we review articles for both objectives.

Virágh et. al. 2013, [4] provided a model of a general autonomous flying robot integrated into a realistic simulation framework. Author suggest that their model can be used to study the behavior of flocking algorithm in regards of cooperation in realistic systems.

Semel et. al 2014 [5], adapted a methodology for grouping methodology in farm animals. A farm with cows was used for their case study. A visual recognition techniques and UAV system control are used. They study rely on the ability of the system to visually identify targets on the ground. They used Convolutional Neural Network (CNN) to process video images captured using UAVs.

M. Thomas, 2013[6] developed a mobile based emergency communication system which will enhance searching for missing persons. Also, investigate the major reasons that render people missing, with the quest to provide a viable technology-based solution to each one of them. The study investigated the processes of locking for missing people during the shortest time possible. More recently, the abductions of kids and adults have reawakened people interest about missing people. Authors encouraged, the police and civilian organizations dealing with missing people have to frequently reviewing their policies and are planning to enhance coordination of their work. This work propose an algorithmic management of information.

A. Nagaty, et al.,2013, [7], presented the design of a fixed-wing UAV. A target detection and localization method is proposed for the developed UAV. The hardware construction, along with the selection of necessary components, is introduced. In order to facilitate modular code development and integration of control laws with simulation and hardware, a hardware-in-the-loop simulator is proposed. The flight control law is developed and tested using the hardware-in-the-loop simulator. Wi-Fi is used for monitoring the state variables of the aircraft.

I. Colomina, P. Molina, 2014[8], presented review of the unmanned aircraft, sensing, navigation, orientation and general data processing developments for UAS photogrammetry and remote sensing with emphasis on the nano-micro-mini UAS segment.

Bhardwaj et al. 2016, [9] had shown UAV-based glaciological studies are gaining pace in recent years due to their advantages over conventional remote sensing platforms. UAVs are easy to deploy, with the option of alternating the sensors working in visible, infrared, and microwave wavelengths. The high spatial resolution remote sensing data obtained from these UAV-borne sensors are a significant improvement over the data obtained by traditional remote sensing. The cost involved in data acquisition is minimal and researchers can acquire imagery according to their schedule and convenience. They discussed significant glaciological studies involving UAV as remote sensing platforms.

Yuan Q et al [10] presented a multi-drone system featured with a decentralized model predictive control (DMPC) flocking algorithm. A drone compute and adjust its position according to its neighbors and update its velocity using this algorithm. The study conduct numerical simulations befor field tests.

S. Prisznyák [11] has focused on the development of UAVs and elaborated on the regulations affecting the small-size devices, which are the most widespread. It present introduction of their potential use in law enforcement, with special focus on the protection of prisons. Also discussed what hazards are involved in the illegal use of drones concerning jails, and what response can be given to these new challenges.

III. MODELLING AND SOLUTION METHODOLOGY

Set of drones modelled as a swarm and behave intelligently through their alignment and information sharing. All drones take-off and land from/at one point (the base station). Each drone moves either randomly or as a member of a swarm. When it is in the air, each drone first aligns itself with other drones to have its vision none overlapped. Then, each drone counts the number of targets (using given technology) appearing in its vision. How to avoid scan area than once and aggregate the total number of entities is the objective of this study.

Drones should cooperate to count the total number of targets within the whole area. Two scenarios are proposed in this study to collect and share information: online and offline. In online, flying drones are connect in mesh Wi-Fi network and share their detection and scanned information in real time among them. While offline sharing is done at the base station when they landing back.

A drone collects information in form of tuples *I(xc, yc ,r, c)* on each snapshot, where *xc* and *yc* are the coordinates of the drone in the field being scanned (view center), *r* is the radius of the view, and *c* is the number of targets seen within current view.

Drones maintain a shared digital whiteboard corresponding to the ground region to exclude the area scanned before. Information is synchronized among drones to let each of them updates its copy of the board. Digital whiteboard also used to estimate the number of targets within current view that are calculated before. It is only needed if the total count of targets is aggregated online.

Whiteboard is implemented as a two-dimensional array of bits called the world where each element corresponds to a squared area of ground called the patch. A value of an element is zero or one and it refers to whether a corresponding patch has been scanned before or not respectively.

Each drone projects and shades the scanned view every time it does a shooting. It should inform other drones about shading. Shading is changing the value of all elements within view from zero to one. The shading process is shown in algorithm 1. In this case, all drones tracking the remaining or non-scanned area within the field.

In algorithm 1, a matrix element is set to 1 if the Euclidean distance from its position to the view center is less than the vision radius.

Algorithm 1: shade(xc, yc ,r)

Input: xc, yc and r are the coordinate and radius of the drone's view.
W[][] the status of the ground (digital whiteboard).
Output: W [][] the new status of the ground

```
for i=x-r to x+r
    for j= y-r to y+r
        let d = sqrt((xc − i)^2 + (yc − j)^2)
                    // Euclidian distance to view center
        if(d<=r)                // within view circle?
```

W[i][j]=1 //shade patch
endif
endfor
endfor

Each drone maintains its own local counter of targets Ck which is initialized to zero at the takeoff moment. Then Ck is increased at each shoot by t; a value of seen entities proportional to a non-shaded area of its vision as explained by(1):

$$\boldsymbol{t} = \boldsymbol{c}\frac{\boldsymbol{s}}{\boldsymbol{\pi r^2}} \quad (1)$$

Where, c is the number of targets seen within current shoot, s is the non-shaded area from the current shoot computed according to an algorithm (2) and πr^2 is the area of drone's vision that is calculated once on the initialization step. All drones return to a base station when whole whiteboard is shaded.

Algorithm 2: getNonShaded(xc, yc ,r)

Input: xc, yc and r are the coordinate and radius of the drone's view.
W[][] the status of the ground (digital whiteboard).
Output:
Let s=0
for i=(xc-r) to (xc+r)
for j= (yc-r) to (yc+r)
let $d = \sqrt{(xc-i)^2 + (yc-j)^2}$
if((d<=r)and(W[i][j]=0))
s=s+1
endif
endfor
endfor

Finally, the expected total number of targets T in the whole regions is calculated in the base station through the summation of all drones' counters as shown in (2)

$$\boldsymbol{T} = \sum_{k=1}^{n} \boldsymbol{C_k} \quad (2)$$

Where, n is the number of drones, C_k is the subtotal of targets detected by drone k.

However, calculation can be made offline at the base station. In this case, drones should return to the base station after a predefined number of shoots, which can be determined empirically. Drones should buffer all gathered information in a table having the header is xc, yc and c and its rows is instances of all snapshots. Finally, the base station merges information from all drones into one table D. Then T is computed according to an algorithm (3).

Algorithm 3: offline calculation of targets

Input: D table of all snapshots of all drones
Initialize W //digital whiteboard matrix
Let T = 0
Let r is the drone vison radius
area=πr^2
foreach item of D Do //item is a tuple of xc, yc, r, and c.
let s = getNonShaded(xc,yc,r)
T=T + (c.s/area)
shade(xc,yc,r)
End foreach
Return T

To proceed to the second objective, we present drone movement algorithm. Hence, a drone behaves according to some rules that control its actions involve take-off, alignment, snap shooting, and moving. These actions are composing an algorithm that governs a drone behavior.

Algorithm 4 show the drone movement behavior.

Algorithm 4: drone's behavior

Input: r is vision radius
X1,Y1, X2,Y2 the field boundaries
W[][] digital white board(shared)
area =$r^2 * \pi$
While (W not completely shaded) or (duration> 0) do
// first predicate for online, second for offline
//Moving
let E =set of patches around the position xc, yc by radius r and their value=0
if E $\neq \phi$ *and mode = online*
let p one-of E
move-to p
else
if distance ahead to the edge of world < vision
rotate right random 360
forward double r
endif
//Scanning
let c= count targets in vision
let s =getNonShaded(xc,yc,r)
Set C = C + c. s / area
shade(xc,yc,r)
end
endwhile
return to base station and provide final C

To keep monitoring the stability of the number targets, the whole process is carried periodically (daily for example for animal groups or whenever there is a risk or a need to do so.

IV. RESULTS AND DISCUSSION

The behaviors of a proposed system is simulated using NetLogo 5.3 which is an agent-based simulation tool developed by Uri Wilensky [12]. The interface of the simulated model is shown in Figure 1. Parameters are set using sliders. The role and scope of each parameter are explained in the next section.

A. Parameter Setting

Different experiments have been conducted using different parameter settings that are summarized in Table 1:

- Field Area: Region dimensions could be adjusted to correspond to some real region. For our tests, the default dimension 32 x 32 patches have been chosen.
- Targets are normally distributed at random in the region. The number of targets has no effects on the model behavior except for the validation issues.

Table 1: Parameters Settings

Targets(entity)	#Drones	Vision radius(km)
50	1	1
100	2	2
200	3	3
1000	5	3

- One also has to determine the number of drones that have to engage in the scanning process. This value should be taken with respect to many management factors parameters like the cost of devices and time required to scan the region, and the vision area. Cost is institute issues. . Thus, three values have been tested; say 1, 2, 3 and 5.
- The vision radius of a drone is a technical parameter. However, three values are considered: 1, 2, and 3km.

Scanning time depends, of course, on the area of the region and how long drones' batteries could be last and then the recharging is required. However, none of these constraints is considered in this work.

B. Results

Many experiments have been conducted to assess the validity of suggested UAVs cooperation model and the impact of the studied parameters. The designed interface for the simulation is shown in fig 1.

In general, the model always converges to approximately the correct number of targets each scanning round. Accordingly, we can say that it success in searching and monitoring for targets in predefined field. However, the convergence time effected by most parameters. The flying time has a direct impact on the energy required for drones to complete the mission before returning to the base station.

The process develop the number of targets calculated each shoot of drones during the tour. Fig 2 and 3 show the number of targets according to the different drone number and vision radius respectively. Here, experiments consider 200 entities.

Several running of each experiment show that the model does not always produce an approximately correct number of targets when there is few drones or a drone uses short vision radius.

Increasing both the number of drones and the vision radius help collecting more information within a short time. However, number of drones imposes more cost and vision radius imposes different detection technology.

When drones share information online, they can avoid pre-scanned regions to accelerate the scanning process. In fig. 4, the number of the counted targets are developed in about 500-time units. Drones are trying to avoid miss regions in their way of scanning, see fig. 5. In this experiment, the number of targets is 1000.

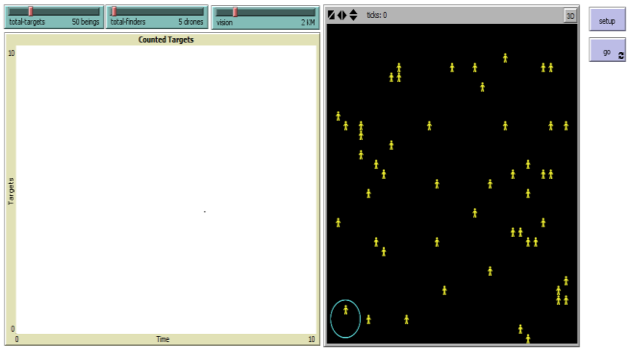

Figure 1: Interface of the simulated model and parameter setting

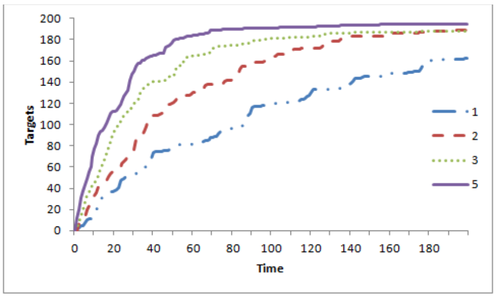

Figure 2:The Impact of drones' number on the solution convergence

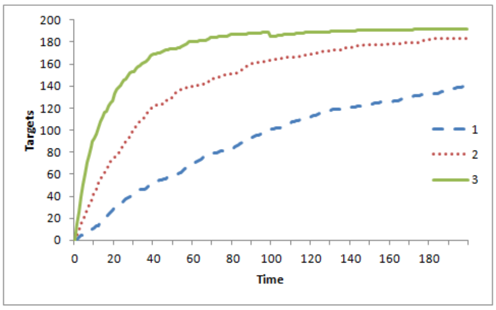

Figure 3: The impact of view radius on the solution convergence

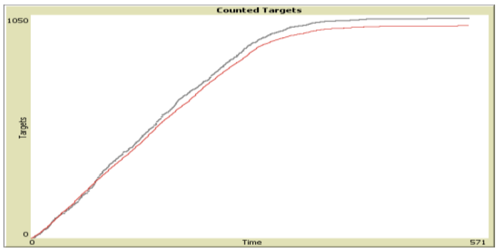

Figure 4:Online count of targets and rate of scanned area

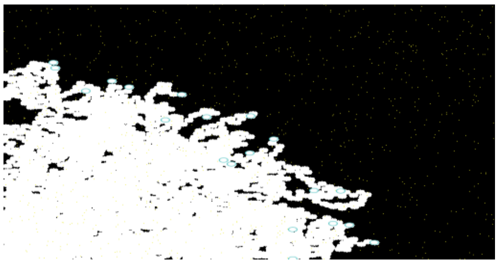

Figure 5:cooperative drone movements

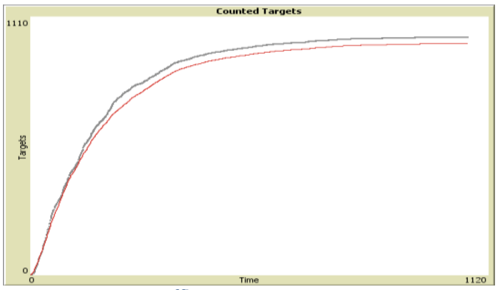

Figure 6: Offline targets counting progress

It is clear from fig. 6 that offline mode takes longer time (about double) than online mode to complete scanning mission.

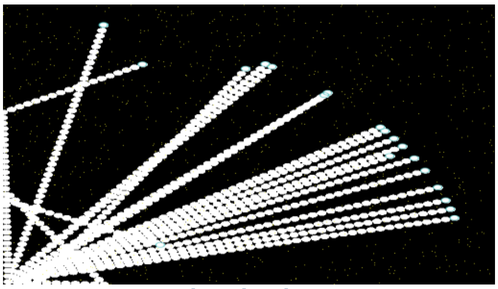
Figure 7: Independent drone movement

Fig 7 show that UAVs move freely and do not share information. This may be considered good option for reducing energy of communication. However, a drone may rescan pre-scanned regions more than once by itself or by other drones.

V. DISCUSSION

Set of UAVs are considered cooperative multi-agent group when they are become autonomous and cooperative to achieve one global mission. We presented a model that is simple and robust for an agent behavior. Results show that cooperation can reduced operation time. However, it highly dependent on technical properties of the UAV. The precision of getting correct number of targets in the UAV's view is key point of success scanning. In the subject of energy economization of UAVs, it is always a tradeoff between time of scanning and communication. However, the model implementation requires device-specific details for making decision choosing either online or offline mode.

VI. CONCLUSION

In this paper, we proposed a model for letting UAVs help much in finding targets effectively in a wide or inaccessible area. Though the numbers of UAVs and their technical features have the essential role of fast convergence of number of found targets to the expected one, the cooperation among UAVs makes the solution fault tolerance. Hence, when one of the drones is crashed others continue the mission and bring the correct information.

We showed that even when online converges the solution rapidly, offline mode could be used as an alternative when reliable communication is not available. Other parameters such as the impact of technical features on energy economization may be considered as perspective for this study.

VII. REFERENCES:

[1] Sud, Ajay. "UAVs and Counter UAVs Technologies in the World and the Indigenous Capability." CLAWS Journal, vol. 13, no. 1, 2020, pp. 65-84.

[2] Hodgson, J., Baylis, S., Mott, R. et al. « Precision wildlife monitoring using unmanned aerial vehicles". Sci Rep 6, 22574 (2016). https://doi.org/10.1038/srep22574

[3] Semel B, P, Karpanty S, M, Vololonirina F, F, Rakotonanahary A, N "Eyes in the Sky: Assessing the Feasibility of Low-Cost, Ready-to-Use Unmanned Aerial Vehicles to Monitor Primate Populations Directly" Folia Primatol 2020;91:69-82. doi: 10.1159/000496971

[4] Virágh, Csaba & Vásárhelyi, Gábor & Tarcai, Norbert & Szörényi, Tamás & Somorjai, Gergő & Nepusz, Tamás & Vicsek, Tamás. (2013). Flocking algorithm for autonomous flying robots. Bioinspiration & Biomimetics.

[5] Chamoso P., Raveane W., Parra V., González A. (2014) " UAVs Applied to the Counting and Monitoring of Animals" In: Ramos C., Novais P., Nihan C., Corchado Rodríguez J. (eds) Ambient Intelligence - Software and Applications. Advances in Intelligent Systems and Computing, vol 291. Springer, Cham. https://doi.org/10.1007/978-3-319-07596-9_8

[6] M. Thomas , " Using A Mobile Based Communication System To Find Missing People", Master thesis, College of Biological and Physical Sciences School of Computing and Informatics. Kenya, 2013.

[7] A. Nagaty, C. Thibault, M. Seto, M. Trentini and H. Li, "Construction, modeling and control of an autonomous Unmanned Aerial Vehicle for target localization," 2013 IEEE International Conference on Robotics and Biomimetics (ROBIO), Shenzhen, 2013, pp. 1544-1549. doi: 10.1109/ROBIO.2013.6739686

[8] I. Colomina, P. Molina, "Unmanned aerial systems for photogrammetry and remote sensing: A review", ISPRS Journal of Photogrammetry and Remote Sensing, Volume 92, 2014, Pages 79-97, ISSN 0924-2716

[9] Anshuman Bhardwaj, Lydia Sam, Akanksha, F. Javier Martín-Torres, Rajesh Kumar, "UAVs as remote sensing platform in glaciology: Present applications and future prospects", Remote Sensing of Environment, Volume 175, 2016, Pages 196-204, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2015.12.029.

[10] Yuan Q, Zhan J, Li X. Outdoor flocking of quadcopter drones with decentralized model predictive control. ISA Trans. 2017 Nov;71(Pt 1):84-92. doi: 10.1016/j.isatra.2017.07.005. Epub 2017 Jul 11. PMID: 28709654.

[11] S. Prisznyák, "Drones and Jails. Scientific Bulletin, 23(1), pp. 43-52. 2018, doi:10.2478/bsaft-2018-0006

[12] U. Wilensky, "Center for Connected Learning and Computer-Based Modeling," Northwestern University, 1999. [Online]. Available: http://ccl.northwestern.edu/netlogo/. [Accessed 2017].