Modelling and simulation of a new cooperative algorithm for UAV swarm coordination in mobile RF target tracking

Yannis Spyridis[a], Thomas Lagkas[b,c], Panagiotis Sarigiannidis[d,*], Jie Zhang[a]

[a]*Department of Electronic and Electrical Engineering, The University of Sheffield, Sheffield, UK*
[b]*Department of Computer Science, International Hellenic University, Kavala Campus, Greece*
[c] *South-East European Research Centre (SEERC), Thessaloniki, Greece*
[d]*Department of Electrical and Computer Engineering, University of Western Macedonia, Kozani, Greece*

Abstract

Recent advancements in sensor technology have allowed unmanned aerial vehicles (UAVs) to function as sensing devices in cooperative aerial communication networks, offering novel solutions in applications of environment inspection, disaster detection and search and rescue operations. Towards this trend, the efficient deployment and coordination of UAV networks is of vital importance. Generating controlled experimental conditions to implement and evaluate different approaches in this context can be impractical and costly and thus the solution of modelling is often preferred. This paper introduces a tracking model in which multirotor UAVs, equipped with received signal strength indicator (RSSI) sensors, are organized in a swarm and cooperate to approximate and trail a moving target. The proposed algorithm is able to offer autonomous tracking in large scale environments, by utilising just the strength of the communication signal emitted by a radio frequency transmitter carried by the target. A model of the proposed algorithm is created, and its performance is thoroughly evaluated in a specialized simulator developed in the Processing IDE. Results demonstrate the increased tracking efficiency of the proposed solution compared to a trilateration method.

Keywords: Simulation, Modelling, Unmanned aerial vehicles (UAVs), UAV Swarm, Mobile Target Tracking, RSSI, Wireless Sensor Networks

1. Introduction

The proliferation of unmanned aerial vehicle (UAV) technologies has allowed the emergence of sophisticated solutions in several areas such as environment monitoring [1], smart cities [2], disaster management [3], surveillance [4], relay networks for services in Internet of Thing (IoT) architectures [5], and search and rescue operations [6]. In several of these scenarios, detecting and tracking an individual is of utmost importance, in order to deliver the required services.

Considering that communication can be often deprived in emergency scenarios in particular, traditional centralized solutions are not always available and the need for decentralized approaches arises. In this context, the vision of the IoT has recently seen a rapid advancement towards the realization of smart solutions that can be feasible in highly dynamic and infrastructure-less environments [7]. IoT architectures can offer context awareness [8], localization [9], and tracking services [10], that can prove vital in emergency situations and can operate when centralized solutions are not preferable. In several emergency situations, such as natural disasters, fires, shipwrecks or similar accidents, there is an immense impact that raises the challenge of providing swift and efficient monitoring and coordination. In this context, an autonomous and efficient group of UAVs is of critical importance, as it can be rapidly deployed and search for victims, providing required communication services while also broadcasting their location to dispatch a rescue party.

There are multiple approaches for dealing with the problem of localizing and tracking a mobile target. Existing methods include visual features [11], radio frequency (RF) time of arrival [12], angle of arrival [13], time difference of arrival [14], Doppler and direction of arrival [15] and received signal strength indicator (RSSI) [16, 17] sensors.

Algorithms that utilize visual features are quite effective for tracking an object in a wide range of tracking scenarios, however they might face difficulties in long range

*Corresponding author.
Email addresses: ispyridis1@sheffield.ac.uk (Yannis Spyridis), tlagkas@cs.ihu.gr (Thomas Lagkas), psarigiannidis@uowm.gr (Panagiotis Sarigiannidis), jie.zhang@sheffield.ac.uk (Jie Zhang)

search and track operations, in cases where the vision is obstructed or when light conditions are not suitable [18]. The use of thermal cameras can tackle this issue, but may introduce many false positives when the weather is warm [18]. In addition, time of arrival and similar methods require more sophisticated antennas when compared to simple RSSI sensors, they often display difficulties in synchronization issues and may restrict the UAV's mobility.

Taking into consideration energy constraints that are crucial in UAVs, a simpler approach is often preferred to ensure that the flight time is increased, and the mission can be carried out in the available time limit. RSSI techniques can offer promising solutions in that regard. However, the key challenge of signal attenuation in the communication channel caused by shadowing, needs to be addressed.

This paper introduces a new strategy, by which multi-rotor UAVs equipped with RSSI sensors form a swarm and collaborate to track a moving target of interest, carrying an IoT device that is periodically transmitting the sensor's information. The proposed technique is able to coordinate the mobility of the swarm, based only on the RSSI measurements received at each UAV, all of which exchange information and harmonize their movement accordingly, with the goal of approximating and trailing the mobile RF source at a close distance. For the signal propagation modelling, the adopted model is derived from the report in [19], which is shown to provide more accurate estimates of the signal's strength in moving networks, compared to free-space and log-distance models.

The introduced scheme offers real-time autonomous tracking, and it can operate when centralized solutions are not available and where previously engineered infrastructure does not exist, providing a potential solution in several emergency scenarios, like the ones mentioned above. The nature of this technique offers the advantage of allowing the UAVs to preserve proximity to the target, without knowledge of its position or estimates of the current distance, which are often erroneous. In contrast to similar methods, the proposed solution can achieve tracking in large scale environments, being restricted only by the received signal strength and the sensitivity of the UAV-mounted RF antenna (example range: 3 km in diameter). Simulation evaluations demonstrate the increased efficiency of the introduced scheme when compared to trilateration-based solutions.

The rest of the paper is structured as follows. The next section presents related approaches in the field of localization, outlining background research on tracking using UAV networks. Section 3 describes the key features of the tracking scheme and presents the propagation scheme used for the signal path loss model. The proposed algorithm is introduced and analysed in section 4. Section 5 provides a simulation evaluation, discussing the results and providing a comparison of the proposed solution with trilateration-based techniques. In section 6 the paper is concluded, and prospective future work is projected.

2. Related Work

The area of mobile target tracking has attracted a lot of interest over the years, with several approaches being proposed in the literature. Networks of UAVs equipped with various sensors have been increasingly used, as their deployment can lead to novel solutions in localization applications. Robust localization techniques usually involve the use of visual sensors to detect and track a moving object. These methods are exceptionally effective; however, they require execution of real-time image recognition algorithms, greatly affecting the energy preservation which is crucial in UAV distributed systems and thus are out of the scope of this paper.

A popular method that has been traditionally used for localization is that of triangulation. Triangulation schemes use the calculated angles between known locations and combine them with distance estimates from the target to form triangles in order to determine its location. A similar approach is that of trilateration, which uses only the distance measurements, calculating the position of the target by the intersection of the formed circles. The authors of [20] propose a network of UAVs equipped with electronic surveillance sensors that provide the RSSI of an RF emitter. These values are used to compute the distance from the source based on a log-normal shadowing model. A fusion center gathers this information from the UAVs and calculates the position of the RF emitter by performing trilateration. The conducted simulation analysis verifies the effectiveness of the scheme when the target emits at high frequencies.

Using optimal control for searching and tracking problems has been also extensively studied, with several control schemes being proposed in recent literature that define the movement of agents in order to track a mobile target effectively. In [21], the authors propose an algorithm that uses combinatorial optimization and optimal control, by combining integer linear programming for obtaining a global optimum with nonlinear programming for analysing the motion constraints of the UAV. A motion planning algorithm is introduced in [22], where a group of UAVs cooperatively track a target by optimizing their intercommunication and sensing with a remote base station. The objective is to find the balance between gaining maximum information through sensing and increasing the probability that robust communication can be achieved with the base station. Simulation results demonstrate that transmission optimization is a factor that can considerably enhance the fusion process and the target estimation accuracy.

An interesting approach is introduced in [23], where the authors propose a model predictive control algorithm that allows a swarm of UAVs to localize cooperatively a RF source. The UAVs are equipped with simple RSSI sensors and determine the optimal future path based on a receding horizon approach. The estimates are determined by an Extended Kalman Filter and the UAV trajectory is optimized by the D-optimality criterion. A similar approach is followed in [24], where a receding horizon control algorithm is introduced for performing multiple target localization. The authors utilize ergodic theory for planning the trajectory of multiple agents, adjusting the information distribution with adaptive bearing measurements in real time.

The authors in [25] exploit the probe requests periodically broadcasted by Wi-Fi devices, such as mobile phones, and devise a strategy for estimating their user's location. In the proposed method, a UAV extracts the RSSI and the physical address of the Wi-Fi device from the broadcasted probe requests, while moving in different locations, known by GPS. A machine learning algorithm is then used to classify the position of the device into an area among predetermined location zones. This technique demonstrates decent accuracy in determining the correct zone, although the corresponding geographical area must be known in advance and partitioned into appropriate zones, so that the algorithm is trained accordingly.

The key distinction of the method proposed in this paper from the techniques discussed above, lies in the fact that it does not try to calculate an estimate of the target's position to achieve tracking. Instead, it utilizes knowledge about the signal strength indicator at each UAV, designing a strategy that will lead the swarm close to the target and enable the UAVs to maintain proximity. The novelty of this approach provides the advantage of not relying in distance measurements, which are inevitably inaccurate due to signal variations caused by random fading effects.

3. Important features of the tracking scheme

This section describes the key features of the proposed tracking scheme, devised to provide the solution to the cooperative target tracking problem. Subsection 3.1 provides the description of the key elements in the system, and subsection 3.2 analyses the path-loss model used for the RSSI measurements.

3.1 System Model

The major components of the system are the following:

a) **Mobile Target:** This is a mobile individual carrying an IoT device. It can also be any moving target with an attached RF emitting device.

b) **IoT Device:** This is an IoT device carried by the target, or any embedded system with an integrated sensor, using an interface that broadcasts the sensor's information.

c) **Tracking Agents:** These are autonomous multi-rotor UAVs that search for the target and maintain proximity in order to offer assistive services (e.g. delivery of medicine or communication services). They are equipped with omni-directional antennas for receiving the target's radio signal and a suitable wireless network interface to exchange information with each other. The UAVs identify their own position by a Global Navigation Satellite System (GNSS) receiver and are equipped with a simple flight control system that allows them to maintain constant speed and altitude. This flight control system also allows them to steer at designated angles and fly towards a specific GNSS location.

d) **On-board Processing Unit:** This is an embedded system with an appropriate wireless network interface, that is carried by the UAVs and establishes connectivity between them. This system also provides the processing capability required to execute the cooperative tracking algorithm in real time and controls the navigation of the UAVs.

3.2 Received Signal Strength Analysis

The technique proposed in this paper is based on the signal strength measurements received by each UAV, and thus the RSSI mathematical formulation needs to be discussed. Empirical data have shown that the signal cannot be accurately modelled by the free-space propagation scheme, due to further attenuations caused by various environmental conditions. In order to model the variation in the received power precisely, the path loss is estimated by adopting a signal propagation model proposed in [19], which was derived from actual measurements in a mobile network of fast entities. In the conducted experiments, the entities were moving at high velocities in a rural area, and the connections were primarily in line of sight conditions. This model was chosen because it applies to long distances, considers line of sight conditions, and is mainly based on velocities corresponding to the UAV speeds in this tracking scenario. A comparison between the free-space and the adopted model is illustrated in Fig. 1. The authors of [19] determine that the path loss of the signal propagating in moving networks that are deployed in outdoor environments can be accurately modelled by the following equation:

$$PL = 41.1log_{10}(d) + 17.2 + 20log_{10}(f/5), \quad (1)$$

where d is the distance between transmitter and receiver in meters, and f is the frequency in GHz.

To get the RSSI at the tracking UAV, the path loss, the target transmission power, and the antenna gains are taken into consideration, using the equation below:

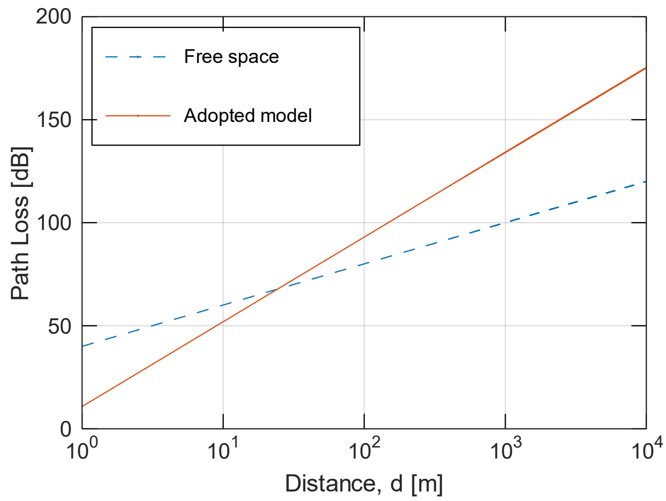

Fig. 1: Comparison of the free-space and the adopted RF model. The dashed line represents the path loss according to the free-space propagation scheme. The solid line depicts the path loss according to the adopted RF model.

$$RSSI = P_{Tx} - [41.1 log_{10}(d) + 17.2 + 20 log_{10}(f/5)] + G_{Tx} + G_{Rx}, \tag{2}$$

where P_{Tx} is the target transmission power in dBm, and G_{Tx} and G_{Rx} are the transceiver's and receiver's antenna gains, respectively.

After substituting the values of the transmission power of the target's transceiver (10 dBm), the gain of the transceiver's and receiver's antenna (2 dBi), and after setting the frequency to 2.4 GHz, the RSSI value as a function of distance is calculated in terms of dB, as displayed in (3):

$$RSSI = 3.17 - 41.1 log_{10}(d) \tag{3}$$

In the considered scenario, the UAVs fly in an open environment where there are not many obstacles that can cause multipath propagation; however, the issue of shadowing still remains. To accommodate for the effect of slow fading caused by this issue, a Gaussian random variable with mean $\mu = 0$ and standard deviation σ is added to the final RSSI value.

4. Tracking Algorithm

The key objective of the UAVs in the proposed scheme is to approach the target and follow it at a close distance. This section introduces a simple and reliable method, that utilizes information about the signal strength at each UAV and coordinates the movement of the swarm accordingly, to accomplish this objective. The proposed solution is achieved in two phases that are analysed in the following subsections. In the first stage, called "Individual Search Phase", the purpose of each UAV is to scan the area for a sufficiently strong signal and, once identified, to notify the rest of the UAVs, so that the cooperative tracking process can commence. Following this, the UAVs proceed to the second stage, called "Cooperative Tracking Phase", where the tracking algorithm is used to coordinate their movement in order to approximate the target. The RSSI sampling time occurs at a 0.5 sec interval in both phases, as this was shown to offer the most optimal results.

4.1 Individual Search Phase

In this phase, the search area is first divided into sectors, according to the number of available UAVs. Assuming the swarm is composed of R UAVs with $R \geq 3$, the area is segmented into R circular sectors each subtending $\theta = 360/R$ degrees. Each UAV starts to move in line with the bisector of the equivalent segment, until the condition for proceeding to the next phase is satisfied. This condition is met, when at least one UAV reaches an RSSI threshold which is ten times stronger than the RSSI at the next closest UAV to the target (approximately 15 dBm higher). This threshold was decided after examining several values, and it was shown to offer the best results. Fig. 2 illustrates an example in which the condition to terminate the individual search phase is satisfied. In the scenario depicted, the swarm consists of three UAVs and the search area is therefore divided in three sectors, with each UAV moving along the bisector of its own segment. When UAV A measures the RSSI value of -100dBm, the other two UAVs measure -115dBm and -125dBm, respectively. Since the difference from the next closest UAV

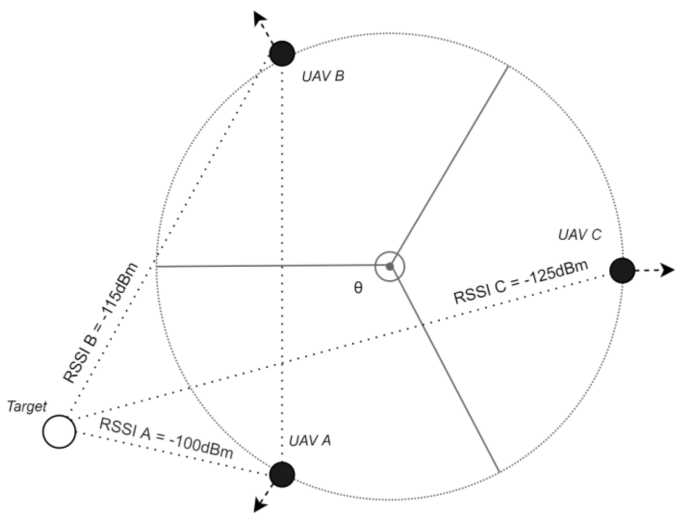

Fig. 2: Individual search phase with 3 UAVs. UAV A satisfies the condition for the swarm to proceed to the cooperative tracking phase.

(in this case UAV B) is 15dBm, the individual search phase is completed. The corresponding RSSI threshold is calculated by (3). It should be noted that not all UAVs ought to complete the individual phase for the swarm to proceed to the second phase. When the first UAV concludes the initial phase, all the rest change to cooperative mode. Small variations in the starting time of the cooperative phase do not affect the overall performance of the tracking scheme.

4.2 Cooperative Tracking Phase

After a UAV satisfies the terminal condition of the Individual Search Phase, all UAVs switch to the Cooperative Tracking Phase and start swarming towards the target. Employing measurements of the received signal strength, the developed algorithm ensures that the UAVs are able to close in to the target and maintain proximity.

The concept lies in the difference in RSSI values measured over time. Increases in the signal power suggest that the UAV is approximating the target and needs to maintain the current course. On the other hand, decreases in RSSI constitute an indication that the UAV is moving away, and thus a decision for a new direction is required. This decision is affected by the knowledge regarding each UAV's current status with respect to the target proximity, and their relative positions in the swarm, as demonstrated later.

To compensate for the fluctuations of the signal due to shadowing in the communication channel, an additional technique is utilized, according to which there are several consecutive signal strength measurements stored in a Samples Window (SW), and the final RSSI figure to be examined is calculated as the mean value of these samples. However, due to the high distances involved in this scenario, a fixed window size is not appropriate for all occasions. Too many measurements result in higher accuracy of the final mean value, but also take more time to be measured, during which the target may have moved further. On the other hand, fewer measurements result in a quicker decision but at the cost of less accuracy. Thus, a new function is defined, according to which the size of the SW changes dynamically based on the received signal, and therefore the current proximity to the target.

Algorithm 1: Determine UAV State

```
while cooperative_tracking_phase = true do
  sample_average ← 0
  j ← 1
  while j ≤ 2 do
    RSSI ← 0
    i ← 1
    while i ≤ window_size do
      RSSI[i] ← getRSSI
      sample_average[j] += RSSI[i]
      i++
    end
    sample_average[j] /= window_size
    j++
  end
  if halted = false then
    if sample_average[0] > sample_average[1] then
      getting_close ← false
    else
      getting_close ← true
    end
  end
end
```

The mathematical relation between the absolute value of the RSSI (x) and the size of the SW $f(x)$ was determined through simulation evaluations and is the following:

$$f(x) = 12log_2(x) - 65 \quad (4)$$

The integer part of this function's outcome is the calculated window size (SWS). After the computation of two consecutive mean RSSI values, the algorithm examines their difference and classifies the UAV, as presented in Algorithm 1.

The goal of this procedure is to determine the UAV's current state regarding the proximity to the target. A positive difference classifies the UAV into the "getting close" state, whereas a negative difference indicates the "getting away" state. If the UAV has managed to approach the target into halt distance, the "halted" state becomes true and it stops moving, hovering in the current location. This information is communicated to all UAVs in the swarm and allows each UAV to take a movement decision based on Algorithm 2.

The first step towards taking the direction decision is the calculation of the maximum RSSI value throughout the swarm, flagging the corresponding UAV as the "warmest". If the current state of a UAV is "getting away", the algorithm compares its current RSSI to the global maximum. In the event that the current RSSI is higher, the UAV steers towards the "warmest" UAV in order to approximate the target, otherwise it takes a fixed rotation.

Algorithm 2: Determine UAV Direction

```
RSSI ← getRSSI
maxRSSI ← getGlobalMax
warmest ← getWarmestUAV
if getting_close = false then
  if RSSI < maxRSSI then
    Change direction towards warmest
  else
    Rotate
  end
end
window_size ← getSWS
```

In case that one UAV fails to communicate with any UAV that is currently closer to the target, then the conditions in Algorithm 2 will fail, and that UAV will follow its individual strategy, rotating until it will start approaching the target. In the event that a UAV fails to receive an RSSI measurement, the algorithm regards this situation as if that UAV has received a very highly negative measurement. As a consequence, this UAV considers that it is very far from the target and rotates to move towards a different UAV in the swarm, specifically to that which has communicated the strongest measured RSSI. This behaviour ensures that no single UAV in the swarm will diverge very far from the target or the rest of the swarm.

In order to prevent the UAVs from colliding with each other during the cooperative phase, the swarm is incorporating a collision avoidance strategy, based on the known locations of the UAVs. According to this strategy, during every RSSI measurement each UAV is checking the distance from the rest of the UAVs and is set to halt if that distance is below 10 meters. It is assumed that the UAVs fly at a high altitude, in an open environment with no other obstacles. Thus, no additional obstacle avoidance method is required, besides the collision avoidance strategy implemented to prevent them from colliding with each other.

This cooperative distributed approach allows all UAVs to take decisions through their onboard processing unit, by executing the same algorithm, communicating with each other, and coordinating their actions to achieve the common goal of tracking the moving target. As a result of following this algorithm, a flocking behaviour is emerging in the swarm. This behaviour allows the UAVs to approach and trail the target by gradually moving towards a "warmer" location.

5. Simulation Evaluation

A comprehensive evaluation of the introduced tracking scheme was conducted, by developing a specialized simulator, using the Processing IDE [26]. The simulator can be used to evaluate various tracking schemes, while providing a visual representation of the simulated environments, as shown in Fig. 3, and exports the results in a spreadsheet. The simulator also displays information regarding the current target and

UAV velocities, the measured RSSI values, the actual distances and important parameters such as the standard deviation of noise, the size of the samples window and more. The key objective of the conducted simulations was the evaluation of the proposed algorithm by comparing its performance to a reference target tracking approach. The method of trilateration was chosen as reference since it constitutes the foundation of most tracking algorithms.

In order to increase the accuracy of the trilateration process, the recent analysis conducted on [27] was taken into consideration. According to the authors' suggestions, the coordination of the UAVs was adjusted so that they always form a triangle while determining the RSSI, in order to avoid having collinear measurements. At each sampling interval, all UAVs take the measurement of the RSSI from the target in a similar way to the proposed algorithm described above. Afterwards, this RSSI value is converted to distance, using the following formula:

$$d = 10^{(\frac{RSSI_{1m} - RSSI}{41.1})}, \tag{5}$$

where $RSSI_{1m}$ is the RSSI value at a distance of 1 meter and $RSSI$ is the measured RSSI at the current position. Then the trilateration algorithm constructs a circle with radius r equal to the corresponding d calculated at each UAV, and finally calculates the intersection of these circles, which is the assumed position of the target, and where all UAVs move towards.

In the simulations, all UAVs start from the same location and fly in an open area with constant speed and at a fixed altitude. At every execution, the target is placed in a random ground location on a circle with a radius of 3 km. Specific random seeds ranging from 1 to 10 are being used, so that the multiple starting locations of the target remain identical on both tracking schemes. Finally, a random waypoint model is used to simulate the mobility of the target which is moving at 5 km/h, corresponding to the walking speed of an individual. A simulation lifetime consists of several discrete simulation cycles. During each cycle, all entities take a single, distinct decision and action. The cycle starts with the target making a movement according to the mobility model used. Then, each UAV in the swarm executes the tracking algorithm once and

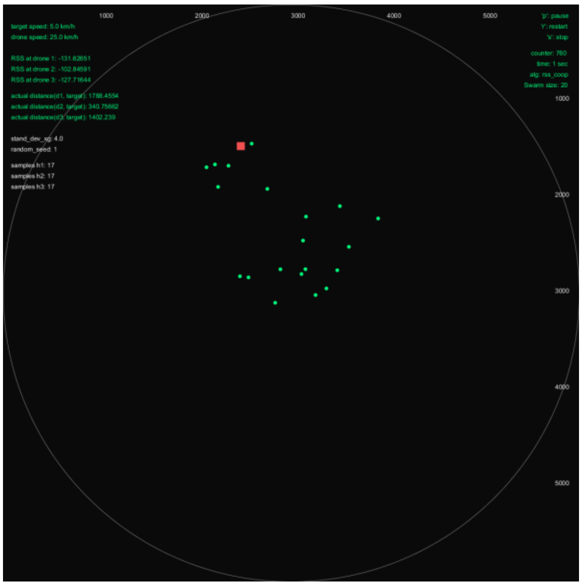

Fig. 3: Visual representation of a devised simulated environment. The square represents the target and the dots represent the UAVs.

advances accordingly. The movement of both the target and the UAVs in each cycle is the minimum amount of movement allowed by the parameters for each case. The parameters of the conducted simulations are listed in Table 1.

The performance of the two algorithms was initially examined as the standard deviation of noise due to fading (σ) is increasing, ranging from 2 to 8. Following this, the performance of the two schemes was examined at a realistic σ value, for different UAV velocities.

The final stage of the evaluation examined the performance of the introduced algorithm for varying target speeds, as well as for larger swarm sizes. The following key performance indicators were used: i) Elapsed Time: The time elapsed until the first UAV is able to approximate the target in halt distance. This distance is used to determine how close the UAVs should approach the target according to the use case. ii) Average Distance: The average distance between the target and the closest UAV throughout the simulation duration. iii) Cycles in Halt: the percentage of cycles in the simulation during which the closest UAV stays still due to the RSSI being in the halt

Table 1: Parameters of the simulation.

Parameter	Value
Environment area	28 km^2
Swarm size	3 - 20
Target speed	5 km/h
UAV speed	25 - 55 km/h
UAV altitude	100 m
UAV halt distance	115 m
Target TX power	10 dBm (10 mW)
UAV RX sensitivity	-92 dBm
Target TX antenna gain	2 dBi
UAV RX antenna gain	2 dBi
Signal frequency	2.4 GHz

threshold (suggestion that it has approached the target). It should be noted that this metric offers an indication of the behaviour of the UAVs. The following metric (cycles in step) shows if the UAV has actually reached the halt distance. iv) Cycles in Step: the percentage of simulation cycles during which the closest UAV stays within the halt distance.

Fig. 4 demonstrates the trajectory followed by 3 UAVs in a scenario with realistic slow fading (σ = 3). From the outlined path it is observed that, despite having no knowledge of the target's location, the swarm is able to effectively approach the RF source using the introduced algorithm, by taking appropriate turns when diverging.

Fig. 5 demonstrates the minimum time required by each algorithm to approximate the target, as a function of the standard deviation σ of the additive White Gaussian Noise. It can be seen that the proposed algorithm is able to maintain efficiency even for high values of σ. Similar observations appear in the chart of Fig. 6, which plots the average distance of the closest UAV from the target. As observed, the proposed algorithm is not greatly affected by increased noise. In contrast, the trilateration solution becomes too inaccurate and fails to provide effective target following, especially as σ exceeds values of 5. The reason behind this observation is that the introduced approach

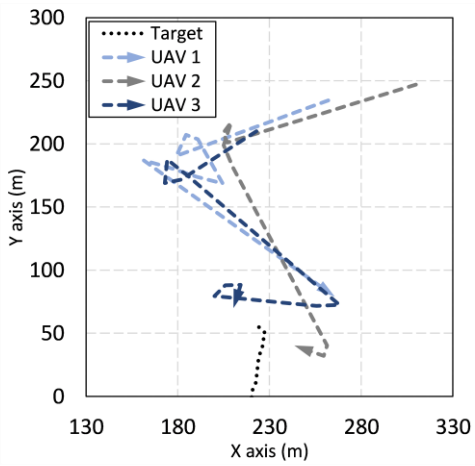

Fig. 4: Target and tracking UAV trajectories.

does not rely in distance measurements obtained by converting RSSI values, like the case of trilateration. Instead, it is based on indicated deviations of the signal's power to provide the required target following capability, which results in more robust performance in random fading conditions.

The charts presented in Fig. 7 and Fig. 8 depict the percentage of cycles in the simulation during which the closest UAV is on halt and stays in step, respectively. When it comes to being in halt, similar results are observed in both algorithms for low noise, with a slight advantage gained by the proposed solution as σ becomes realistic and higher. When examining the actual duration that the UAVs are able to stay within halt distance, the results depict a clear advantage for the proposed algorithm. As these two charts demonstrate, the introduced approach outperforms trilateration for realistic fading conditions and is even able to remain effective in highly noisy environments. This is attributed to the fact that the introduced algorithm guides the UAVs to halt distance, without estimating the target's position, in contrast to trilateration which relies in location estimates based on calculated distances.

The second stage of the simulation evaluation examines how the velocity of the UAVs is affecting the performance of the two algorithms. During this evaluation, the standard deviation of noise due to fading is set to a realistic value (σ=3), as suggested in [19], while the UAV velocities range from 25 to 55 km/h. The results about the

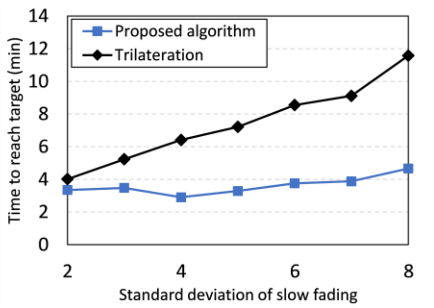

Fig. 5: Minimum elapsed time until the UAV reaches the target versus σ.

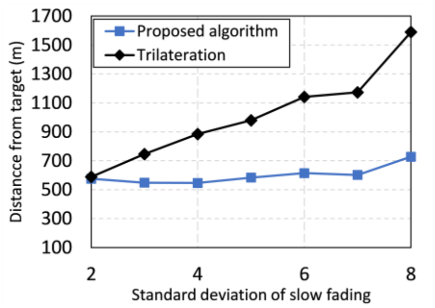

Fig. 6: Average distance between the UAV and the target versus σ.

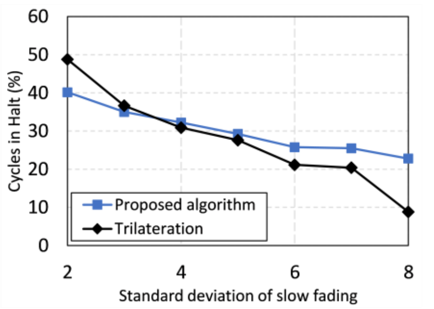

Fig. 7: Simulation cycles percentage during which the UAV stays in halt versus σ.

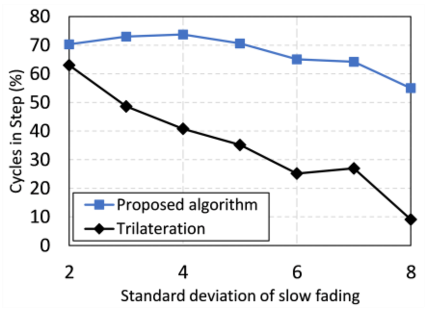

Fig. 8: Simulation cycles percentage during which the UAV stays in step versus σ.

"Elapsed Time" metric are presented in Fig. 9. As expected, an increase in velocity yields shorter time elapsed until the target is approached. In Fig. 10 the chart plots the average distance from the target as a function of the UAV's velocity. It is evident that again, higher velocities lead to shorter average distances. The results demonstrate that the introduced algorithm is more efficient in tracking the target at realistic noise, irrespective of the velocity of the UAVs. It is also observed that the time efficiency of the introduced algorithm does not grow significantly, as the UAV speed increases. The reason is that, while higher velocity has an obvious advantage in terms of time required to reach the target, it also allows the UAVs to move further between direction decisions, which may result in additional diversion from the target, until a movement correction is made by the algorithm.

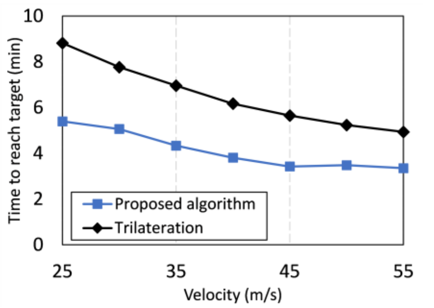

Fig. 9: Minimum elapsed time until the UAV reaches the target versus the UAV velocity.

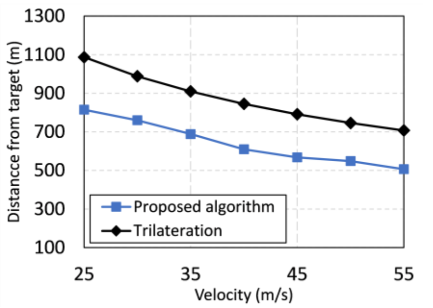

Fig. 10: Average distance between the UAV and the target versus the UAV velocity.

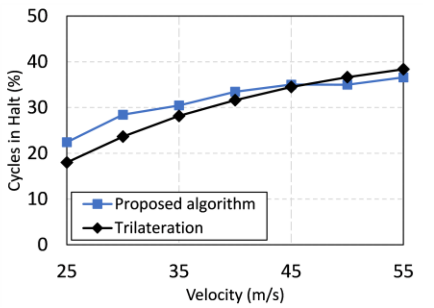

Fig. 11: Simulation cycles percentage during which the UAV stays in halt versus the UAV velocity.

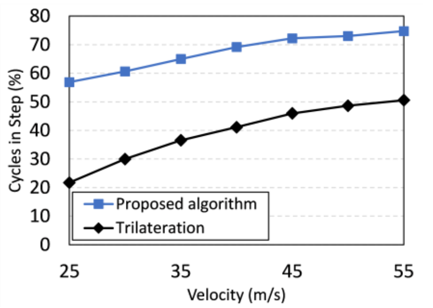

Fig. 12: Simulation cycles percentage during which the UAV stays in step versus the UAV velocity.

Following in Fig. 11, it is observed that in both algorithms the UAVs stay in halt for approximately the same time as velocity increases, while as shown in the chart of Fig. 12, the introduced algorithm clearly gains the advantage in being in step from the target for longer. An interesting observation is that, when it comes to the UAVs managing to reach the target in halt distance (be in step), the proposed solution is demonstrating increased efficiency even at relatively low velocities, with the algorithm being able to keep the swarm close for longer, potentially supporting several energy-constrained applications.

In the final stage of the system evaluation, the performance of the introduced algorithm is inspected for higher target velocities, and the effect of increasing the number of UAVs in the swarm is also examined. Fig. 13 demonstrates the minimum time required to approximate the target as a function of the standard deviation (σ) of the

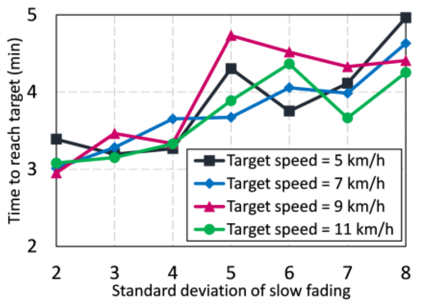

Fig. 13: Minimum elapsed time until the UAV reaches the target versus σ, for different target speeds.

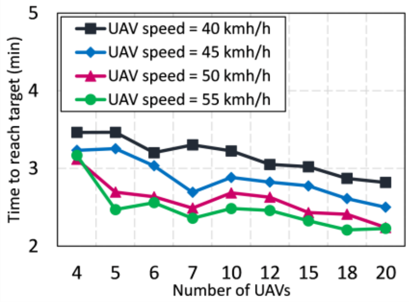

Fig. 14: Minimum elapsed time until the UAV reaches the target versus the size of the swarm, for different UAV speeds.

Gaussian Noise. The velocity of the target ranges from 5 to 11 km/h and the UAV speed is set to 50 km/h. The chart indicates small variations in the performance of the algorithm for the different target speeds which is reasonable considering the relatively much higher UAV velocity. The chart depicted in Fig. 14 plots the minimum time required by the first UAV to reach the target as a function of the number of UAVs in the swarm. For relatively low UAV velocities, the results demonstrate improved performance as the size of the swarm increases. However, as the UAV velocity increases, the algorithm does not seem to be affected in a significant way by a swarm size higher than 7 UAVs. This observation can be justified by the fact that if the swarm consists of a sufficiently high quantity of UAVs, the algorithm is able to divide the search area into an adequate number of sectors during the individual search phase, so that at least one UAV will happen to move inside a territory in which the target will be very close to.

6. Conclusion

This paper presented the model of a new cooperative algorithm, that allows a swarm of UAVs to locate and follow a mobile individual, by employing only measurements of the RF signal power emitted by an IoT device carried by the target. This was achieved by decomposing the task of tracking into the two phases of individual search and cooperative approach. A specialized simulator was developed that allowed the comprehensive evaluation of the algorithm through diverse simulations, demonstrating its increased efficiency in comparison with a trilateration-based solution. The evaluation results have also shown that the introduced algorithm is able to maintain effectiveness in high levels of signal attenuation due to fading and in low UAV velocities as well. Potential applications of this tracking model focus on the provision of communication and location services in dynamic environments when centralised infrastructure is not available. The successful implementation of the proposed scheme implies efficient communication between the UAVs, which is a subject relatively understudied. The survey in [28] offers an extensive review of existing communication protocols for UAV networks and discusses open issues for research. Regarding the introduced algorithm, future work will revolve around the investigation of a multiple target tracking scenario in the context of IoT.

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