Locating a Hidden Transmitter Using Swarm UAVs

Jørgen Nordmoen, Sondre Engebråten, Thomas Thoresen, Espen Skjervold, Lars Landmark, Erlend Larsen and Jonas Moen
Norwegian Defence Research Establishment (FFI)
Postboks 25, 2027 Kjeller
NORWAY

Jonas.Moen@ffi.no

ABSTRACT

The ability to locate a hidden Radio Frequency (RF) transmitter is important in military operations. Moreover, the ability to detect and geolocate transmitters in noisy environments can be very challenging. Since the transmitters are unknown, no assumptions about their radiated effect and frequency can be made, i.e. a hidden transmitter. Efficient collection of data, with minimal human intervention and supervision is particularly important. These scenarios require mobile platforms to enable operations over larger areas with quick response times.

Unmanned Aerial Vehicles (UAVs) are an ideal platform for RF sensors. Since the platform is elevated, line-of-sight is achieved, increasing the system performance.

To locate a hidden transmitter quickly and effectively several agents need to cooperate. Swarm Intelligence (SI) is a term used to describe biologically inspired methods enabling groups of agents to cooperate. SI agents are focused on the global best, but act according to local rules using local communication. This makes the desired goal state an emergent property of the system, making it fault-tolerant, scalable and less reliant on centralized coordination.

This paper presents simulation results that indicate that the geolocation task can be performed with as little as 3 agents. In addition we present both upper and lower bounds for Power Difference of Arrival geolocation, which can be used when studying Swarm Intelligence methods for geolocation.

1.0 INTRODUCTION

The motivation for this work is to lay the ground work for using UAVs to autonomously geolocate, i.e. find the geographical location of, a hidden RF transmitter. In this context a hidden transmitter is a transmitter where the frequency, position and transmitting power is unknown. Such transmitters are abundant in the real world, where different devices contains several transmitters working with different frequencies and transmitting at varying intensities, even changing intensities based on power saving concerns. In a military context most modern radio systems have the ability to quickly change frequency to avoid interference or hostile jamming and can therefore be considered hidden transmitters.

Geolocating hidden transmitters can be used in many military contexts. Examples such as detecting and locating hidden soldiers and intrusion detection around static and dynamic encampments are some of many possible scenarios where using RF geolocation is relevant. However, for such a system to work it needs to be operated autonomously with little to no human intervention. The system needs to be robust against unexpected failure and should be able to scale to different operating requirements.

Unmanned Vehicles (UVs) and especially UAVs have become much more affordable in recent years. Their performance and robustness have also improved to a point where large numbers of UAVs can be deployed in the same environment with little effort. With the speed and maneuverability of modern UAVs, rapidly deploying and searching a large area is now a possibility. UAVs are therefore an ideal platform to utilize.

Amplitude measurements are a simple way to gather information about RF signals. These measurements are easy to collect because of the inexpensive hardware required, in the form of a Received Signal Strength (RSS) indicator. In recent years these sensors have become small and inexpensive enough that almost any UV can be expected to have one. Power Difference of Arrival (PDOA) is based on comparing different amplitude measurements from three or more locations in order to estimate the position of a RF transmitter [16]. By using this technique combined with simple RSS measurements new low-cost UAVs can be used to locate RF transmitters.

Coordinating several autonomous agents can be quite the challenge. A key challenge is how the individual agents should behave when taking into consideration that they are a small part of a larger system. SI and the more specialized field of Swarm Robotics (SR) uses simple agents and emergent behavior to design large scale distributed systems. SI takes inspiration from natural systems [4, 28] and utilizes local communication to achieve swarm level emergent behavior. The promise of SI is the simple agent design, scalability and fault tolerance. Simple agent design require less sophisticated UVs which can be a way to reduce cost. Greater scalability means that the system as a whole can handle different scenarios and is flexible to different operational requirements. Because the system is scalable it must also be fault tolerant, which means that when faults occur the systems ability to maintain the current task is not diminished. In other words, the system should not stop functioning simply because a smaller part has failed. These properties makes SI and SR capable of handling many different tasks [2, 5, 7, 11, 13, 35].

This paper presents the background and simulation study conducted in preparation for real-world experiments. We will first describe the background theory of RF detection, geolocalization, and SR. Then we will describe the simulation study carried out to test behavioral strategies for the UAVs. Results of the simulation study accompanied by a discussion follows before the conclusion is presented.

2.0 BACKGROUND

In this section we will first discuss the challenges surrounding RF signal propagation, detection and localization. Then different techniques for geolocation will be discussed along with requirements for these techniques. We will then conclude this section with background information about SI and SR.

2.1 Signal Propagation

RF signals are electromagnetic waves with a frequency between 3kHz and 300GHz [29]. When RF signals propagate they incur losses. With no external influences the signal is degraded by the free space path loss [29] which occurs because the wave propagates as an expanding sphere, where the power density decreases while the surface area expands.

$$L = \left(\frac{4\pi d}{\lambda}\right)^2$$

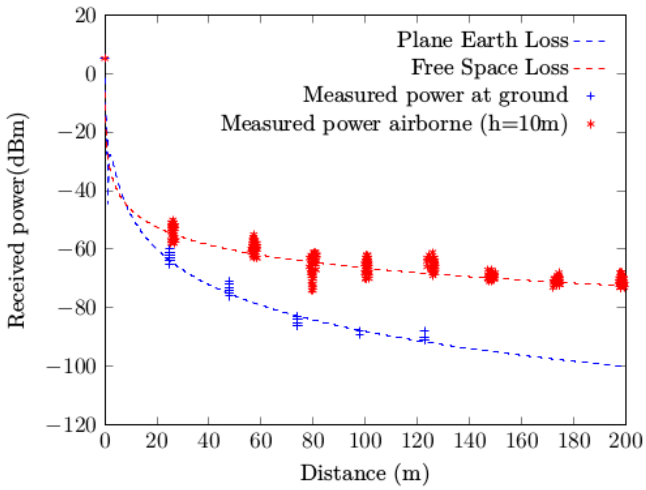
The equation above describes the free space path loss, L describes the loss occurring at a receiver, where d is the distance between receiver and transmitter and λ is the wavelength of the transmitted signal. In real world scenarios the path loss that a signal may encounter is often affected by additional sources. Obstacles, buildings and weather differences all contribute to the path loss of a transmitted signal [16, 29]. Different path loss models exist that model different aspects of the propagation loss. A generalized model is the Log-distance path loss model, shown in the equation below.

$$L(d)_{dB} = L(d_0)_{dB} + 10\alpha log_{10}\left(\frac{d}{d_0}\right) + \chi_\sigma$$

In the equation above the loss, $\mathrm{L(d)_{dB}}$, for a given distance between transmitter and receiver is given by the reference loss $\mathrm{L(d_0)_{dB}}$, i.e. the loss at the transmitter. It is also dampened by 10α, where α

characterizes the propagation environment. With a α of 2 the model is equal to the free space path loss, but α can be varied depending on the desired 'environmental loss'. The signal is also affected by the logarithmic distance between the transmitter and receiver. The final effect is noise, χ_σ, which is a characterization of the noise experienced in the receiver, usually modeled as a normal distribution with σ standard deviation.

Figure 1: Signal propagation as a function of distance. Stars are measurements with receiver elevated 10 meters. Plus's are measurements with receiver at ground level. The frequency used was 2.4GHz. The blue line describes the plane earth loss model and the red line describes the free space path loss. This figure shows that elevating the sensor platform is beneficial for RF performance. Figure adapted from [34].

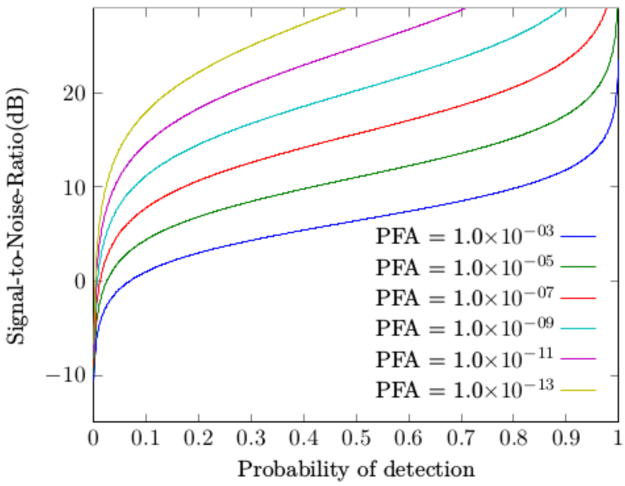


In previous work we experimented with elevated sensors to demonstrate how free space path loss can be achieved using a flying sensor platform. This work showed, see Figure 1, that simply elevating the sensor platform 10 meters above ground resulted in a propagation loss equal to the free space path loss model. This underscores the utility of elevating the sensor platform when performing experiments and demonstrates why are envisioned for real-world systems.

2.2 Detecting a signal

The problem of geolocating a hidden RF transmitter consists of two problems. Before precise location estimates can be made there is a need to detect the propagating RF signal. Once the signal is detected the agent(s) can start collecting samples for processing. These samples can then be processed to estimate the precise location of the transmitter.

Figure 2: Relationship between PFA, SNR and the probability of detection, adapted from [18]. The Figure shows how increasing (or decreasing) the PFA decreases (or increases) the probability of detection for a given SNR.



Detecting a RF signal can be difficult because of the finite sensitivity of receivers. This limitation comes from the fact that a receiver, while sampling a potential signal, will have different sources of noise that adds to the signal [29]. The noise have several different sources [18, 25, 29], such as thermal noise in the receiver hardware and cosmic noise. In order to separate the noise from a transmitted signals thresholding is used. This threshold puts a bound on the Probability of a False Alarm (PFA) and separates out noise in signal classification. The PFA is a measure of the statistical likelihood of a classified signal being additive noise. The main factor in setting the threshold is the expected Signal-to-Noise-Ratio (SNR) and the PFA. SNR affects the threshold since a higher value will decrease the PFA at a given threshold. In other words, as the SNR increases and the ratio between actual signals and pure noise rises, the probability of noise being classified as a signal decreases. It then follows that if the SNR grows the threshold can be lowered accordingly to have the same PFA. This relationship is illustrated in Figure 2. Figure 2 shows how an increase in SNR makes the probability of detection rise and how a change in PFA increases (or decreases) the probability of detection for the same value of SNR.

2.3 Geolocation

Geolocating a hidden transmitter is a difficult challenge [8, 16, 21]. Since neither frequency, position nor transmitted effect is known different techniques have been devised [16]. The different techniques are based on different properties of the received signal. The techniques are listed below in no particular order.

- Angle of Arrival
- Time Difference of Arrival
- Frequency Difference of Arrival
- Power Difference of Arrival

Angle of Arrival (AOA) uses a specialized antenna to estimate which direction the signal is coming from [16]. This technique is often used when using large arrays of antennas to estimate direction. An advantage of this technique is that a single receiver can estimate the direction of the signal, but can not know the distance to the transmitter. When using two receivers the directions can be correlated and a position in two dimensions can be estimated. AOA is well understood and simple to utilize, but the technique requires specialized hardware.

Time Difference of Arrival (TDOA) uses the difference in received time at different spatial locations to estimate the position of a hidden transmitter [16]. By correlating the arrival time at different locations and assuming that the signal propagates at the same speed for all receivers an estimate of the position can be made. This technique requires that all receivers synchronize with a central location which can compare the different arrival times. By using at least three receivers location, estimates can be calculated for a hidden transmitter. This technique produces the best results of the ones listed here, but requires complex time synchronization to produce good results. This technique can utilize omnidirectional antennas.

Frequency Difference of Arrival (FDOA) uses the apparent change in frequency that occurs when the receiver is moving compared to the propagating signal [16]. The frequency is seemingly altered because of the Doppler shift affecting the received signal. By estimating the velocity and direction of the receiver the Doppler shift which should affect a received signal can be calculated and a direction towards the transmitter can be estimated. Using two or more receivers the frequency and Doppler shift can be compared at a central location and a position estimate can be calculated. FDOA suffers from similar problems as TDOA in that bandwidth limitations in the receiver restricts the accuracy of the location estimate in the same way as time resolution limits the accuracy in TDOA. FDOA also requires each receiver to be moving relative to the transmitter when sampling the signal.

PDOA uses the change in received power at different spatial locations to estimate the transmitter position [16]. By combining the difference in received power with a propagation model a central controller can collect samples and correlate these to estimate a position. PDOA is often used in simple, inexpensive systems because of the simple hardware required. This technique does not produce the same accuracy as the other techniques above because of the reliance on a propagation model. However, when using an elevated platform the free space path loss model can often be a good estimate and give good results [34].

There are several different ways of calculating PDOA [16]. In related work, [8, 9], the Non-Linear Least Square (NLLS) method was selected because it is easy to understand and can be implemented computationally efficient. In the equations below the basis of NLLS is illustrated,

$$\overline{P_{kl}} = P_k - P_l$$

$$Q(x,y) = \sum_{k<l} [\overline{P_{kl}} - 5\alpha log_{10}\left[\frac{(x-x_l)^2 + (y-y_l)^2}{(x-x_k)^2 + (y-y_k)^2}\right]]^2$$

here Pk and Pl is the received signal at position k and l respectively, is a characterization of the propagation environment as discussed in section 2.1 and in equation 2, xl, yl, xk and yk is the position where sample l and k were taken. Q(x; y) is a summation over all pairs of samples and is used over a grid of positions that the transmitter can be placed in. This creates a minimization problem as described below.

$$TransmitterPosition_{x,y} = \min_{x,y\,\in\,grid} Q(x,y)$$

The resolution of the grid parameter in the equation above determine the accuracy of the position estimate.

2.4 Swarm Intelligence

This section presents background information for agent design. We will first present foraging which is an active research area within SI to illustrate how decentralization and local information can be used to locate a signal source. We then present another angle, source seeking, which also illuminate distributed search.

2.4.1 Foraging

Foraging is one of the prototypical applications within both SI and SR [2, 4, 5, 6]. The basic premise of foraging is the desire to retrieve or utilize some element(s) of the environment situated in unknown positions. Foraging is inspired by natural systems, such as ant colonies, where animals or insects hunt for food or debris for nest building. Foraging is often used as a task since many elements of foraging can be used in other applications, e.g. locating radiological hazards can be seen as a foraging task where the resource is 'gathered' when it is located. Understanding foraging can therefor help in designing distributed control for cooperative multi-agent teams [24].

Foraging as a task can be performed as individuals and as a collective [24]. In the simplest form each agent need not care about what other agents are doing and can focus on its own performance. This strategy, while simple, often scales quite well and exhibit many properties desirable in SI systems. In separate work done by [10, 12, 19] it is shown that collectively foraging performs better than foraging alone. This indicates that scalable cooperation is important and can increase performance [33].

Social foraging is a term used to describe foraging as a cooperative group. The concept was first described in work by [10] where the authors showed how a few simple concepts could lead to stable foraging in gradient fields. Their work showed that by combining chemotaxis, a simple form of gradient climbing described in section 2.4.2, and repellent/attraction forces it can be shown that swarms can collectively move to more favorable regions and can climb diverse nutrient profiles. Their work was extended by [19] where the inclusion of noise added to both agent interaction and the nutrient profile. This later work showed that stability could be achieved despite the presence of noise. Their work also showed that multiple agents working together can solve the task better than a singular agent. This result is important because it shows that cooperative foraging can overcome noise and solve a complex problem that can be translated to real world problems.

2.4.2 Source Seeking

The goal of source seeking is to detect and locate a source emitting a signal in an environment. Many different types of sources have been studied, but chemical plume tracking is most often used [17]. Source seeking has a close connection with robotic experimentation and much of the early work within the field focused on single robot experimentation [26]. Later this was extended to distributed source seeking [14].

Much of the work within source seeking has been based on different forms of taxis inspired by natural phenomenon. The two most prominent forms have been chemotaxis, a form of gradient climbing [3, 20, 27], and anemotaxis, where agents orient themself according to the motion of fluid around it self [15].

$$direction_t = \begin{cases} direction_{t-1} \pm random(5^o), & C_t \geq C_{t-1} \\ direction_{t-1} \pm random(180^o), & C_t < C_{t-1} \end{cases}$$

The equation abve describes the basis of chemotaxis where the agent will move some distance before using the described equation to select a new direction. Ct is the sensor reading, directiont is the movement direction of the agent at time t and random is a uniform random variable. The behavior will thus try to move in approximately the same direction if moving towards the source, but if no improvement is detected the agent should make larger turns to hopefully detect the source.

In recent years more research have gone into distributed source seeking [1, 17, 36]. Much of the work regarding distributed source seeking have utilized rigid formation control to act like a distributed sensor. Ogren et al. [23] used a combination of Artificial Potential Field (APF) and a gradient decent algorithm to move in noisy scalar fields. One important contribution of this work was to show that if the swarm contract and expand in response to the scalar field they could easier tolerate noise. Another important work was Zarzhitsky et al. [37] which contributed a new form of distributed taxis, called fluxotaxis. Their work built on previous work, [30, 31, 32], to create a stable formation of agents which could then search for a source by collectively solving the fluid flow problem.

3.0 SIMULATOR

To test how geolocation can be performed distributed on a collection of UAVs we conducted several simulations with different behaviors.

To test the different algorithms a simulator framework was setup based on Repast Simphony [22]. Repast is a general multi-agent simulator designed to be easy to extend and with the capabilities to simulate many agents.

The simulator was setup in such a way that the agents are placed in one corner of the environment and a transmitter is placed in the center of the environment. The distance between agent starting location and transmitter can vary, but for the experiments carried out here, were kept at a fixed distance. The experiments assumes that the agents can detect the transmitter, i.e. they can separate the signal from noise, when they start. The propagation model used is the free space path loss model, this simulates elevated sensor platforms (explained in section 2.1). For all the tests we simulate the signal with 1dB of noise. Once the experiment is started the agent are tasked with finding the transmitter. A summary of the simulation parameters can be found in table 1.

During simulation the agents can sample their position and receiver amplitude each tick. These samples are stored after each tick so that we can evaluate the strategies after their run has ended.

Table 1: Simulation parameters.

Parameter	Value
Repetitions	50
Simulation seconds	5000
Simulation steps	50 000 (10 steps per simulated second)
Transmitter threshold range	Radius 250
Transmitter position	(250, 250)
Agent starting location	Randomly placed between (0, 0) and (10, 10)
Number of agents	3, 4, 5, 6, 7, 8
Speed	1 distance unit per simulated second
PFA	1e-6

4.0 RESULTS AND DISCUSSION

4.1 Power Difference of Arrival Strategy

To show that it is possible to geolocate a hidden transmitter we implemented a simple search strategy based on PDOA. The agents share all samples and periodically calculate PDOA to gain an estimation of where the transmitter is located. This estimate is then distributed to all agents which use this as a reference to move towards. The agents then periodically recalculate the PDOA estimate after a fixed number of simulation steps. This allows the agents to gather new samples that are spatially different from the previous. In addition the strategy employs a simple collision avoidance routine based on APF. This prevents the agents from clustering in the same position which is important when the agents approach the transmitter [9]. By clustering on-top of the transmitter the strategy would limit sample collection and prediction accuracy would decrease. The behavior of the strategy is illustrated in Figure 3.

To evaluate the search strategy we collect samples from all agents for all simulator ticks and process these. To determine how well the strategy has performed we calculate PDOA on the collected samples. This is equivalent to all agents transmitting their samples to a central coordinator, which then calculates PDOA in order to locate the hidden transmitter. Since PDOA is very computationally expensive, given many samples, selection of the 40 best samples seen so far is used. By choosing the best samples this selection is biased towards samples closer to the transmitter which result in better prediction accuracy.

Figure 3: *Log* probability of finding the agent in the search area for the PDOA strategy. The number of agents used is 3.

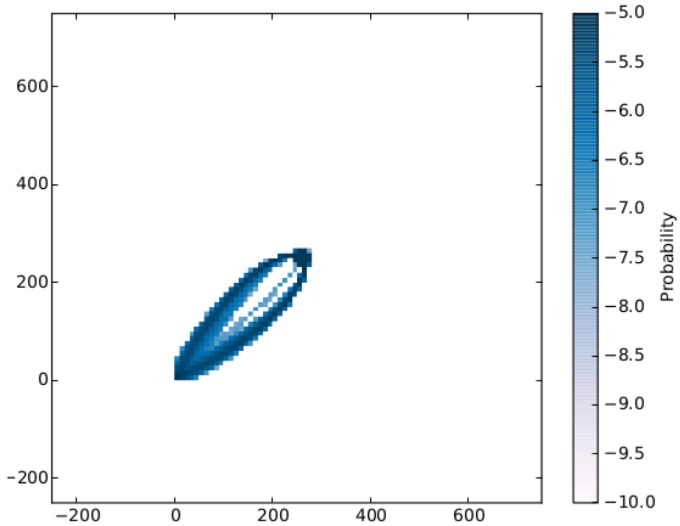
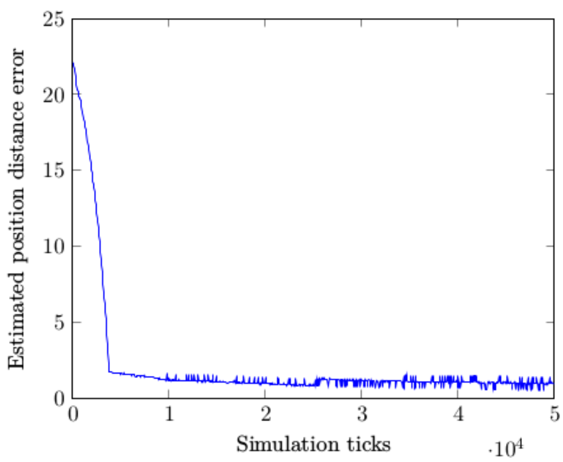


Figure 4: Average performance, over 50 simulations, of the PDOA strategy for 3 agents.

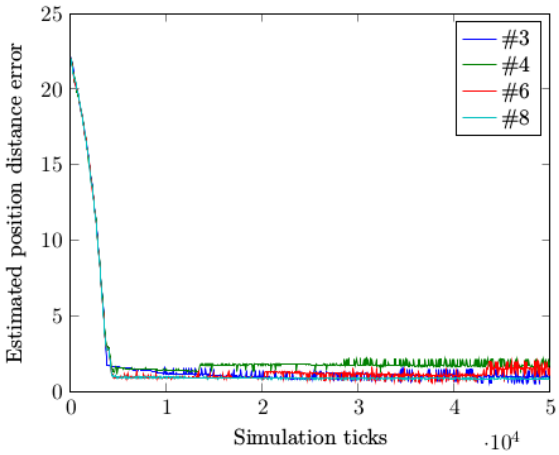


In Figure 4 we show the results of the PDOA strategy. The plot shows that by sharing all position information between agents we can reliably geolocate the transmitter[1]. The plot is the average of all 50 simulator runs using 3 agents.

From Figure 3 we can see that the movement of the PDOA strategy is close to a straight line towards the transmitter. This means that the search strategy is close to optimal performance. Which means that the result in Figure 4 is close to an upper bound for any search strategy when using the PDOA algorithm.

The results in Figure 3 and 4 show that using the PDOA strategy with 3 agents can solve the problem of geolocating a hidden transmitter. Since the number of agents deployed can have an impact on the results we tested with several agent configurations. In Figure 5 the performance of the different agent configurations are shown.

Figure 5: The effect of number of agents on the PDOA strategy.



The results in Figure 5 show that there is a slight increase in performance when more agents are used. However, this effect is only apparent when an even number of agents are employed. This indicates that another effect is influencing the results. Since the PDOA strategy utilizes a simple collision avoidance strategy the difference is most likely attributed to differences in how the agents cluster around the transmitter once they have arrived. From previous work [9] it is apparent that the way the agents cluster around the transmitter can greatly influence the estimation error. Therefore, the difference in performance is not due to the number of agents, but is an artefact of the number of agents combined with the collision avoidance algorithm.

The results shown so far demonstrates that practical real-world demonstrations are possible using as little as 3 UAVs. However, this relies on a situation where the UAVs share all information. In military application this sharing of information is vulnerable to several sources of interference. It is therefore interesting to explore other possible search strategies for the geolocation.

4.1 Limited Communication Strategies

If sharing all information is impossible the most basic strategy to employ is a purely **random strategy**. This strategy moves in a randomly chosen direction until the signal is lost. Once this happens the agent turns back in the direction where it last had a signal. This direction is the perturbed to introduce random movement. In addition to testing a random search strategy we also implemented a simple hill climber based on **Chemotaxis**, as described in equation 6. This strategy is well known in the source seeking literature which makes it a good first approximation to searching without sharing information.

[1] It is important to note that the offset from 0 in the figure is due to the grid resolution of the PDOA algorithm.

Figure 6: *Log* probability of agent position for the random strategy and Chemotaxis. The number of agents used is 3 for both strategies.

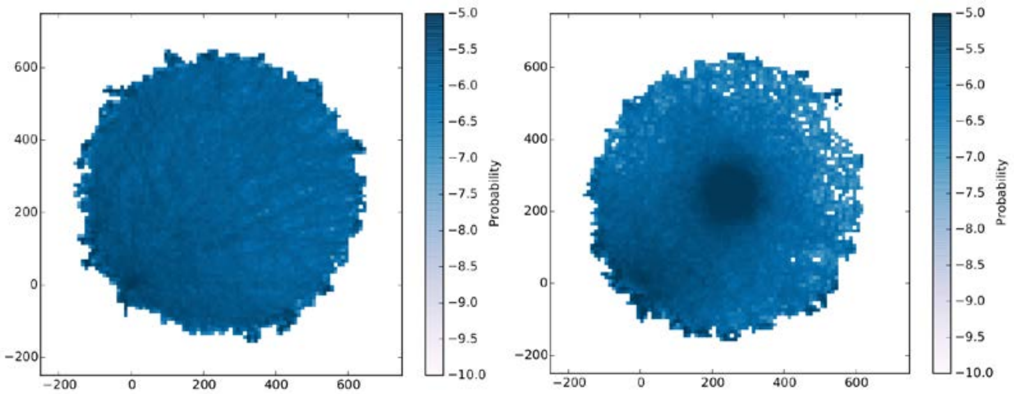
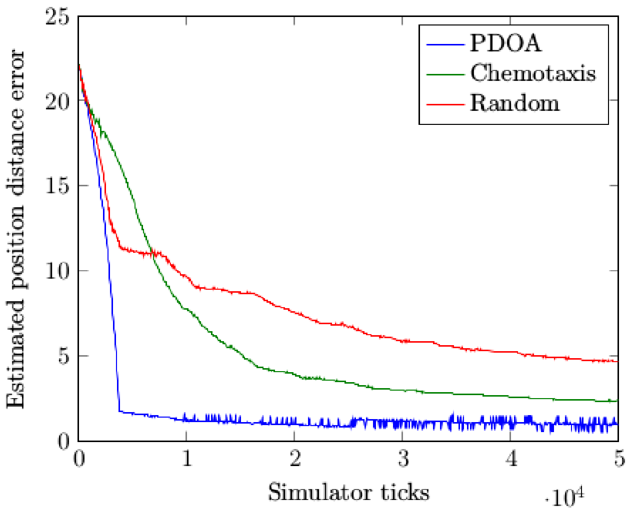


Figure 6 shows the logarithmic probability of where it is likely to find an agent for the given strategies. From Figure 6a we can conclude that the random strategy manages to stay within the threshold boundary of the transmitter. In Figure 6b we can see that the Chemotaxis strategy explores a larger area than the PDOA strategy, Figure 3, but unlike the random strategy, Figure 6a, is more concentrated closer to the transmitter.

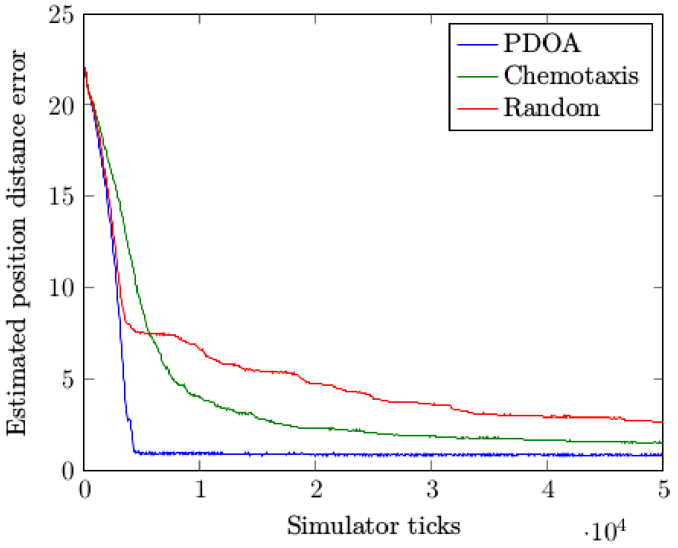
The result from the three different search strategies are shown in Figure 7 and 8. This shows that of the three search strategies tested the PDOA strategy still outperforms the other two. This is also true for the other agent configurations, not shown for brevity. These results are interesting because they place an upper and lower bound for the achievable performance when geolocating based on the PDOA algorithm. These upper and lower bounds are interesting because they create a context in which other search algorithms can be placed.

Figure 7: Comparison of search strategies with 3 agents.



Another interesting observation from the results in Figure 7 and 8 is the difference between the random search strategy and Chemotaxis at the start. It can clearly be seen that the random search strategy performs better initially compared to Chemotaxis. This is a result of the way the random strategy searches in straight lines. The result indicates that coming close to the transmitter is beneficial and quick exploration should initially be preferred.

Figure 8: Comparison of search strategies with 8 agents.



We have also compared the performance using the Mann-Whitney U-test. The results show that, for all agent configurations, the PDOA strategy differs from the two other strategies with $p < 0.05$. Together with Figure 7 and 8 this shows that the PDOA search strategy is statistically better compared to the other search strategies.

5.0 CONCLUSION

This paper lays the ground work for future testing and it is our intention to transition the results from simulator to real-world UAVs. Taking the PDOA search strategy and transitioning it into real-world experiments is achievable using low cost UAVs and simple RSS hardware. Furthermore, since we have created a upper and lower bound for the geolocation task research into SI algorithms for geolocation is very relevant. Other challenges such as transmitters capable of moving and intermittently transmitting are also relevant areas of research.

We have shown three different methods for using RSS measurements to locate an hidden RF transmitter. Two of these strategies, random and Chemotaxis, do not require communication between agents. This can be a significant advantage, both in terms of scalability and in minimizing the signature of the agents.

Furthermore, we present a near optimal bound for performance of PDOA geolocation using a number of agents. This can be used in further studies as a benchmark for comparing new SI geolocation methods.

Finally, the work presented here shows that as little as 3 agents are sufficient to successfully locate a hidden transmitter. This is promising for the viability of a real-world, low cost, autonomous SI system for locating hidden transmitters.

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