Multi-Cluster Agent-Based Emitter Geolocation using Hough Transform Data Fusion

Alexander Mikhalev and Richard Ormondroyd
Department of Informatics and Sensors
Cranfield University, The Defence Academy of the UK, SN6 8LA, UK
Email: a.mikhalev@cranfield.ac.uk

Abstract—This paper is concerned with the use of multi-platform agent-based emitter geolocation. Multiple, self-aware, agents representing different types of emitter location method, naturally form clusters, which are controlled by the network connectivity. Each cluster provides a fusion hierarchy: each agent is able to geolocate individually, a cluster of agents can refine the emitter position using fusion and multiple clusters can further refine the position estimate by taking advantage of the different view of the target by each cluster. In this paper, the benefits of providing fusion between clusters of self-aware agents are examined and the advantages of such clustered agent-based data fusion are demonstrated for the scenario where imperfect communication forces the sensor platforms to operate as multiple clusters.

Keywords: Geolocation, data fusion, agent-based, cluster, Hough Transform.

I. INTRODUCTION

In earlier papers [1] [2] [3], a new method of emitter geolocation was presented that was based on image processing techniques rather than the more usual classical methods using triangulation and hyperbolic location [4] or statistical methods [5] [6] [7]. The new method exploits the properties of the Generalized Hough Transform and one of its key features is that it is able to fuse different types of measurement data (such as angle of arrival measurements (AOA), time difference of arrival measurements (TDOA) and frequency difference of arrival measurements (FDOA)) by transforming them into conditional probabilities and storing them in a unified parameterized space. Once in this consistent framework, they can then be fused easily.

In order to optimize data fusion using this method, an extension to the method was described in [8] wherein sets of measurements are weighted according to the impact that they have on the positional error rather than simply according to the measurement error. In this way, the weighting includes the effect of the geometric dilution of precision (GDOP) of a particular geolocation method. The results cited in [8] showed that this reduced the error of the position estimate.

It was also shown in [8] that the Hough Transform has properties that can be exploited which allow it to be used as a framework for agent-based fusion, thus connecting low level measurement fusion to higher, more ‘abstract’, levels that can be used for decision making. Furthermore, using the method of self-weighting, it is possible to provide each geolocation agent with a method to calculate their contribution to the final goal of emitter geolocation; thus creating the concept of ‘self-aware’ or cognitive agents.

The paper [8] considered the case where all the agents were constrained to operate within a single cluster due to restrictions placed on the information exchange by the wireless communications network that they shared. In this paper, we take the concept of cognitive agents one step further where agents naturally form multiple clusters. Each cluster is assumed to consist of multiple self-aware agents where communications is assumed to be good. However, communications between clusters is assumed to exist, but is sporadic. This creates a fusion hierarchy: each agent is able to geolocate individually, a cluster of agents can refine the emitter position using fusion and clusters of agents can further refine the position estimate by taking advantage of the different view of the target by each cluster. In this paper, we examine the benefits of providing fusion between clusters of self-aware agents.

II. AGENT-BASED EMITTER GELOCATION

In [8], the concept of agents was applied to the problem of emitter geolocation using the Hough Transform space as the model of the environment, where the common goal of the agents was the geolocation of the emitter. An agent is characterized by some, or all, of the following properties [9]:

- **Autonomous Behaviour**: Every agent is characterised by autonomous behaviour.
- **Individual World View**: Every agent has its own model of the external world that surrounds it which maybe incomplete or even incorrect.
- **Communicative and Cooperative Capacity**: Intelligent agents can exchange information with other intelligent agents and this is how it builds up its own world model. Communication with other intelligent agents is the pre-condition for common action in pursuit of a goal.
- **Intelligent Behaviour**: Intelligent Agents have the capability to learn, make logical deductions to modify their own world model in the light of new information that is supplied to it, or which it obtains from the environment.
- **Spatial mobility**: Intelligent agents are sometimes required to display spatial mobility.
• Strategies and Decentralised Control: Agents should be able to develop individual strategies to ensure the achievement of a common goal, even without central regulation.

• Emergent Behaviour: Cooperation (feedback) and interactions between intelligent agents can produce a stable system that displays new global behaviour on the next higher level of abstraction.

In the context of the emitter location problem, the agent does not simply represent the sensor platform. Rather, it represents the ability of one or more platforms to provide a position estimate according to a particular method. For example, two platforms are necessary to take a TDOA measurement and this corresponds to a single agent capable of geolocating using TDOA measurements. The same pair of platforms may, independently, make a frequency difference of arrival (FDOA) measurement and this will correspond to a second agent capable of geolocating using FDOA measurements. A platform may be able to make bearing only measurements and this produces an agent that geolocates using AOA.

In the pursuit of the common goal of emitter location, these agents use the ability of the Hough Transform to weight their individual contributions to the collaborative fused estimate and communicate this to the other agents or central control.

III. THE AGENT’S LOCAL MODEL OF THE WORLD

Each agent generates a local model of the emitter location problem. Here three types of agent are of interest: (i) those that locate emitters using AOA, (ii) those that locate emitters using TDOA and (iii) those that locate emitters using FDOA. In the following sections, these models are briefly described.

A. Geolocation using Angle of Arrival

Consider a single mobile platform, whose position is accurately known, that is able to measure the AOA of the emitted signal periodically using an interferometer or antenna array. Let the measured AOA at some instant be \( \theta_i \). The conditional pdf, \( p(x, y|\theta_i) \), of locating the emitter at some point, \((x,y)\), assuming that the measurement error in the angle of arrival is Gaussian distributed, is given by:

\[
p(x, y|\theta_i) = \frac{\exp\left(-\frac{(\xi-\theta_i)^2}{2\sigma_{\theta_i}^2}\right)}{\sqrt{2\pi}\sigma_{\theta_i}}
\]  

where \( \xi \) is the calculated angle from the current position of the platform, \((x_r, y_r)\), to the point \((x,y)\) and \(\sigma_{\theta_i}\) defines the standard deviation of the AOA measurement.

Although the point \((x,y)\) could lie anywhere within the search space, in practice, the search space is split into a regular grid and \((x,y)\) is constrained to lie at one of the grid points and is evaluated at each of these grid points.

The local world model of this AOA agent is updated every time it makes a new measurement and this model is built as follows from (1):

\[
A_{AOA}(x, y) = \frac{1}{M} \sum_{m=1}^{M} p(x, y|\theta_m)
\]

where \(M\) represents the total number of measurements made. This accumulated pdf now represents the voting array for the Hough Transform.

An example of such a local world model is pictured in figure 1. This shows the probability of locating the emitter using only two AoA measurements that intersect at a very shallow angle. The peak indicates the likely position of the emitter.

B. Geolocation using Time Difference of Arrival

Assume that the emitter signal of interest is received at two spatially separated receivers, \(r_1\) and \(r_2\), whose positions are known. The TDOA, \(\tau_{1,2}\) between these receivers can be obtained using signal cross-correlation, or some other delay-estimation technique. In this case, the pdf of the emitter location evaluated at a point \((x,y)\) given \(\tau_{1,2}\), and assuming Gaussian distributed timing errors, is given by:

\[
p(x, y|\tau_{1,2}) = \frac{\exp\left(-\frac{(R_{1,2}-c\tau_{1,2})^2}{2\sigma_r^2}\right)}{\sqrt{2\pi}\sigma_r}
\]

where \(R_{1,2}\) is the difference between the range of a particular point on the grid \((x,y)\) to receiver 1 and the range from the same grid point to receiver 2, \(c\) is the speed of light and \(\sigma_r\) is the range error for this measurement. A method of calculating \(\sigma_r\) is discussed in [2] and [8]. The local world model of this TDOA agent is built as follows from the conditional pdf (3) using

\[
ATDOA(x, y) = \frac{1}{L} \sum_{l=1}^{L} p(x, y|\tau_{1,2,l})
\]

where \(L\) represents the actual number of TDOA measurements taken and \(\tau_{1,2,l}\) is the \(l\)th time difference of arrival measurement. \(ATDOA(x, y)\) is equivalent to the voting array (accumulator) for the Hough Transform for the TDOA measurements.

An example of the agent’s local world model is shown in figure 2 using a single measurement of \(\tau_{1,2}\) for a particular separation of the two sensor platforms.
C. Geolocation using Frequency Difference of Arrival

Assume that the emitter signal of interest is received at two spatially separated receivers \( r_1 \) and \( r_2 \) whose positions are known. The \( i \)th FDOA measurement \( f_{di} \) can be obtained using a Doppler receiver. In this case, the pdf of the emitter location evaluated at a point \((x, y)\) given \( f_{di} \), and assuming a Gaussian distributed frequency measurement error, is given by:

\[
p(x, y | f_{di}) = \frac{\exp\left(-\frac{(D_{1,2} - f_{di})^2}{2\sigma_{f_{di}}^2}\right)}{\sqrt{2\pi\sigma_{f_{di}}}} \tag{5}\]

where \( D_{1,2} \) is the frequency difference between the Doppler measurements calculated from a particular point on the grid \((x, y)\) and receiver 1 and the Doppler measurement from the same point on the grid and receiver 2. \( \sigma_{f_{di}} \) is the standard deviation of the measurement error for FDOA. The method of calculating \( \sigma_{f_{di}} \) is discussed in detail in [8].

The local world model of this FDOA agent is updated every time it makes a new measurement and this model is built as follows from (5):

\[
A_{FDOA}(x, y) = \frac{1}{N} \sum_{m=1}^{N} p(x, y | f_{di}) \tag{6}
\]

where \( N \) is the number of measurements.

Figure 3 shows an example of the local world model for 20 FDOA measurements. The sensor platform positions move with time, so the figure shows the most likely emitter position (i.e. the peak value) after these measurements have been fused. This figure clearly shows how an FDOA agent is able to geolocate using a pair of moving platforms.

D. A Method of Weighted Fusion

When fusing different measurement types, it is usual to weight the individual contributions of the measurements according to their measurement error [6]. However, for emitter geolocation, the problem is extremely non-linear and the effect of the measurement errors on the position error is augmented by the GDOP for that emitter/sensor platform scenario. It is important to recognize that each type of measurement (AOA, TDOA and FDOA) provide their own, different, contributions to the GDOP and simply weighting according to measurement error does not represent the true impact of the error on the positional accuracy of the emitter position estimate.

In [8], a novel form of obtaining the weights was proposed, where the aim was to compensate for the different contributions to the emitter position error from each of the different measurement types according to their GDOP, for that scenario.

\[
A(x, y) = \frac{w_{TDOA}}{L} \sum_{l=1}^{L} p(x, y | \tau_{l,1}) + \frac{w_{AOA}}{M} \sum_{m=1}^{M} p(x, y | \theta_{m}) + \frac{w_{FDOA}}{N} \sum_{m=1}^{N} p(x, y | f_{di}) \tag{7}
\]

where, \( w_{TDOA} \), \( w_{AOA} \) and \( w_{FDOA} \) are the weights for the three types of measurement which are calculated according to the impact that both the measurement variance and GDOP has on them. This is achieved directly from the accumulated pdfs of the Hough Transform.

In this case the accumulated pdf for a particular measurement type, such as TDOA, given by (4), is first normalized by its peak value, as shown in figure 2, and then thresholded at some appropriate value to create a contour at that threshold, as shown in figure 4 for a threshold set at 75% of the maximum. The area contained within this contour, \( S_{TDOA} \), is then obtained. This is repeated for the case of the AOA measurements whose accumulated pdf is given by (2) and the FDOA measurements whose accumulated pdf is given by (6). The areas contained within the respective contours are: \( S_{AOA} \) and \( S_{FDOA} \). It will be clear that the larger the area of the contour, the greater the contribution of these measurements to the positional error and hence a smaller weight is required. The weights are given by:

\[
w_{AOA} = \frac{S_{tot}}{S_{AOA}} \tag{8}
\]
Figure 4. Local world model for TDOA only measurements shown in figure 2, thresholded at the level 75% of maximum likelihood value

Figure 5. Scenario used for agent-based emitter geolocation, showing the flight paths of the different sensor platforms

\[ w_{\text{TDOA}} = \frac{S_{\text{tot}}}{S_{\text{TDOA}}} \]  
\[ w_{\text{FDOA}} = \frac{S_{\text{tot}}}{S_{\text{FDOA}}} \]

where \( S_{\text{tot}} \) is the area of the total search space.

E. Agent-based Data Fusion

In order to illustrate the new method, consider the scenario shown in figure 5. In this scenario, two platforms are moving North at 40m/s according to a wavy path and they are able to take TDOA measurements (Agent 1), whereas the platform moving East at 40m/s is only able to take AOA measurements (Agent 2). This represents a cluster of AOA, and TDOA agents. The standard deviation of the TDOA measurement error in this simulation is set at \( 7 \times 10^{-7} \) s and the standard deviation of the AOA error was set at a realistic value of 0.02 radians. The true target position is at (93km,63km). Figure 6 shows the cluster-level world model for AOA and TDOA agents after a total of 30 measurements have been taken along the respective flight paths. The peak in this model shows the most likely position of the emitter. Figure 7 shows how accurately each agent can independently geolocate the emitter using the average rms position error as a metric. In this figure, the average rms error is plotted as a function of the TDOA and AOA measurements taken as the platforms move along their respective flight paths. In order to obtain the average rms error the simulations were repeated 50 times and the average taken. It is clear for this scenario that TDOA measurements generally provide a more accurate position estimate. However, it should be noted that the precise results of rms position error are strongly dependent upon the platform/emitter geometry, and hence the scenario, because this affects the GDOP. This is true for all the results presented in this paper.

Figure 8 shows the benefit of fusing the TDOA and AOA measurements for both weighted and unweighted cases and the results are compared with the case for TDOA-only emitter geolocation. Two observations can be made. First, fusion of the measurements significantly improves the positional accuracy of the geolocation algorithm. Second, the impact of weighting is also clear because the weighted result tends to be much more accurate in terms of rms error.

Figure 9 shows the effect of fusing FDOA with TDOA and AOA for a similar scenario to the previous case. In this case the platforms travelling North are now able to perform TDOA and FDOA measurements so that we now have TDOA agents, FDOA agents and AOA agents. The figure, which is taken for thirty AOA, TDOA and FDOA measurements, shows the cluster-level world model for this situation. It is clear that adding the FDOA measurements ultimately results in improved positional accuracy, compared with the AOA and TDOA result of figure 6. This is indicated by the very sharp peak in the cluster-level world model.\(^1\)

Figure 10 quantifies the results of figure 9 using the rms positional error as the metric. This figure shows quite clearly how both weighted and unweighted fusion improves the positional accuracy of emitter location relative to emitter location by just one type of agent. It is found that after about 30

---

\(^1\) This is not always the case when the number of measurements is relatively few.
measurements, the weighted measurements are more accurate than the unweighted measurements, for this scenario.

IV. CLUSTERED AGENT DATA FUSION

Because the Hough Transform provides a unified environment for the local own-world models of the agents as well as the cluster-level model of the clustered agents, it is possible to apply the same method of weighted data fusion, as described above, at a higher level where there are several clusters of agents. In this case, the Agents within each cluster generate a cluster-level world model for that cluster and this is used to obtain the weight, \( w_{\text{cluster}_i} \), for that cluster (assumed here to be the \( i \)th). These weights are used to weight the cluster-level world models. The overall model is the weighted combination of cluster-level world models, given by:

\[
A_{\text{multi}} = \frac{1}{w_{\text{cluster}_1}} A_{\text{cluster}_1} + \cdots + \frac{1}{w_{\text{cluster}_i}} A_{\text{cluster}_i} \tag{11}
\]

The scenario in figure 11 has been set up in order to illustrate this. Here, three Unmanned Aerial Vehicles (UAVs) are used,
as in the previous scenario, and form cluster 1. In this cluster, two UAVs fly North and follow a wavy path, whilst one UAV flies East. The North flying UAVs act as a TDOA agent and the East flying UAV acts as an AOA agent. In addition, three more UAVs are added to the scenario. One flies in a tight circular path, a second flies in an oval racetrack path whilst the third flies generally in an Easterly direction. The UAV flying along the oval path takes AOA measurements, with an rms error of 0.02 rad whilst the other two platforms act as a TDOA agent with an rms error of $10^{-7}$s timing error. Each cluster has good communications so that agents within that cluster can fuse their results as described above. However, communications between clusters is sporadic. This means that each cluster carries out individual cluster-level fusion, and the clusters can only fuse their cluster levels together when the communications between them is assumed to be good.

Figure 12 and figure 13 show the effect of using two clusters to geolocate a single emitter. Figure 12 represents the rms error of the emitter position for Cluster 1 and figure 13 shows the rms error for Cluster 2. In each figure, the rms positional error is plotted as a function of the number of measurements made in each cluster. This forms the cluster-level world model (this is shown as the red solid line in figures 12-13). Only after this model has been created by each cluster are the two cluster models fused to form a high level model.

The result of fusing the weighted cluster-level models is shown as the red stars in both figures. It is clear that the weighted high-level world model has a much higher accuracy than the weighted cluster-level models for either cluster. Furthermore, the use of cluster level fusion results in a much faster ‘convergence’ of the rms error as a function of number of measurements. The significant improvement in emitter geolocation performance by adopting a cluster-level fusion strategy is most certainly due to the effect of minimising the effect of GDOP by using different ‘look’ directions for each cluster even though the fusion at this level takes place relatively infrequently.

V. CONCLUSION

The paper [8] considered the case where all the agents were constrained to operate within a single cluster due to restrictions placed on the information exchange by the wireless communications network that they shared. In this paper, we have taken the concept of cognitive agents one step further where agents naturally form multiple clusters. Each cluster is assumed to consist of multiple self-aware agents that forms a fusion hierarchy: each agent is able to geolocate individually, clusters of agents can refine the emitter position using fusion and clusters of agents can further refine the position estimate by taking advantage of the different view of the target by each cluster. In this paper, the benefits of providing fusion between clusters of self-aware agents has been examined and the advantages of the clustered (hierarchical) agent-based data fusion has been clearly demonstrated.

REFERENCES