Evidence Based Navigation in Swarms

Duminda A. Dewasurendra[†], Peter H. Bauer, Matthias Scheutz and Kamal Premaratne

***Abstract*— A low-complexity, evidence based navigation algorithm for swarms of mobile sensors is presented. It can be effectively used in scenarios where a particular event signature is characterized by a mix of weak signal modalities with certain degrees of intensity, distributed in a local region. The method is based on Dempster-Shafer (DS) evidence theory and enables the mobile nodes to process temporally ordered sensor data and accommodate imprecise information from multi-modal sensors on board. Local decisions are made based on fused evidence triggering an attractive beacon, which in turn draws other agents for further detection and tracking. Simulation results are presented for a multi-modal signal signature tracking scenario.**

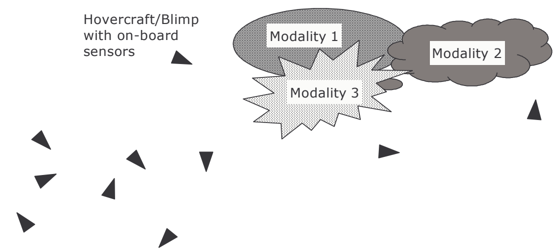

Fig. 1. Swarm of hovercrafts/blimps scanning for a multi-modal signal signature

I. INTRODUCTION

Heterogeneous swarms of extremely simple, physically realizable agents are of great interest for local detection and tracking purposes in both military and civilian applications. In particular, certain applications call for the detection and tracking of a collection of signal modalities or substances present in ground, water or air. For example, consider a disaster management scenario in which a mixture of weak signals is present in a local area indicating heat, smoke, radioactivity, toxic substances, etc. In some cases, the presence of one of these individual modalities itself can raise a flag. On the other hand, the presence of this unique collection of signal modalities in a local area may indicate an important event. The signals can be of unknown strength and the intensities may drift over space and time, making autonomous swarms the ideal candidate for the detection and tracking of such events.

A. Motivation and Goals

This research stems from an application where a swarm of hovercrafts/blimps each with an on-board sensor suite is used to detect and track a unique signal signature characterized by a combination of weak signal modalities in a local area (See Figure 1). In this application, the on-board sensors can detect each of the signal modalities whenever they come in contact with, or are very close to the sensor. In addition, each agent is equipped with an attractive beacon to be activated whenever it successfully detects the event, to bring in other swarm agents to the same area for further scanning. Apart from the basic navigation principles used to maneuver mobile swarm agents throughout the area while avoiding collisions, *their navigational behavior must be partially governed by the sensor signals* in order to locate the event. A notable distinction here is that it is not possible for the mobile nodes to detect the weak signal modalities or substances of interest at a distance, but the agent has to be physically present in the area for detection to be possible.

We assume that the signals are distributed with varying intensities in localized regions. The detection of a small trace of one signal modality alone by a particular node does not constitute a detection and hence is not a cause for turning the attractive beacon on to bring other nodes into the locality. Nevertheless, such an event must create an initial interest for a particular mobile node to search more in the vicinity of this detection. Depending on the application scenario, the event of interest can be characterized either by the mere presence of a particular mix of substances, presence of the mix of substances with certain levels of intensity, or the presence of a unique signal signature denoted by a particular distribution of multiple substances in a local region. Therefore, the data from multiple sensors collected along the path of the mobile agent must be temporally ordered. New incoming multi-modal information must be properly combined with the available evidence with due consideration to the inertia of already collected evidence. Moreover, the uncertainties involved in sensing during flight and the potential inaccuracies of low-fidelity sensors typically used in the low-cost, expendable mobile node platforms pose several challenges in designing robust swarm systems for such applications.

In this paper, as an extension to the threshold based local navigation control scheme presented in [1], we present a robust, evidence-based navigation scheme to address these issues. In [1], the beacon activation is based on a simple, single modality thresholding scheme. We propose major modifications to this scheme based on multi-modal sensor signal processing using Dempster-Shafer (DS) evidence the-

D. A. Dewasurendra and P. H. Bauer are with the Department of Electrical Engineering, University of Notre Dame, Notre Dame, Indiana. M. Scheutz is with the Department of Computer Science and Engineering, University of Notre Dame, Notre Dame, Indiana. K. Premaratne is with the Department of Electrical and Computer Engineering, University of Miami, Coral Gables, Florida. [†]Corresponding author Email : ddewasur@nd.edu

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ory. The goal of this scheme is to use temporally ordered, multi-modal sensor data to detect unique events characterized by the local presence of combinations of weak signal modalities. It can provide improved detection capability and trigger the attractive radio beacon only if certain signal signatures satisfying specified time-modality characteristics are present.

B. Previous Work

Several researchers have discussed probability based navigation schemes for swarms in the past. The research in [2] considers the navigation of a team of UAVs through a battlefield and uses a probability map to represent threats in the area. As the vehicles move, the sensors collect new information about the environment and the existing probability map is updated using Bayes rule. Probability maps for different threats are used to calculate the overall risk map, and it is shared by all vehicles for path planning. As compared to [2], the scheme presented here does not require communication among nodes, and also has lower computational complexity.

The work in [3] focuses on a multi-vehicle cooperative search problem where a team of UAVs seeks to find targets in a dynamic and risky environment. UAVs use a target probability map, a threat probability map, and a certainty map as its knowledge base for the mission. It is assumed that the threat map is known a priori. The target probability map is updated based on Bayesian inference. One major drawback of this scheme is that it requires a priori information on threat probabilities, which is not readily available most of the time.

The research in [4] discusses a scheme for Bayesian updating of the search map using probabilistic information provided by sensors during a cooperative UAV search mission. The information incorporated by the model includes events such as the detection of an object. Important sensor events, such as detecting and discriminating real from false objects are considered.

Local navigational control schemes [5], [6] have several advantages over centralized or decentralized control. They lead to emergent behavior that share many features of general distributed control, but do not suffer from scaling problems since only local neighbors are needed for communication. While most local approaches have low complexity and good fault-tolerance, they still suffer from the consequences of using digital communications. Research in [1] presents a threshold-based ultra low complexity mechanism for local control of UAVs tracking a chemical cloud or plume where neither digital communication nor GPS is required for navigation.

In [1], navigational decisions are based on attraction/repulsion beacons. A mobile swarm agent exploits the beacon signal gradient available across its breadth to navigate itself towards or away from the beacon. The research in [7] discusses a class of attraction/repulsion functions which result in swarm aggregation. It presents the stability analysis for several cases and show that the model can be generalized for formation control. The algorithm presented here is an extension to the scheme in [1].

The rest of the paper is organized as follows: Section II presents an overview of the navigation concept in [1] which this work is based upon. A brief overview of the Dempster-Shafer (DS) evidence theory, and several extensions to it proposed by the authors are given in Section III. Section V presents some simulation experiments for validation of the proposed framework, followed by concluding remarks in Section VI.

II. The Basic Navigation Concept

In this section, we briefly discuss the basic navigation concept presented in [1]. Each swarm agent is equipped with two types of beacons, a *collision avoidance beacon col* (to repel agents from each other and distribute them) and a *target attraction beacon tar* that is only activated when agents detect a target. The *col* beacons are always on and each agent is equipped with a stereo antenna/receiver pair to detect *col* beacons of other agents. In addition, each agent uses the antenna/receiver pair to detect the *tar* beacons of other agents. These *tar* beacons are used to attract other agents to the vicinity, once an event of interest is detected by one agent.

The *col* receivers can indirectly extract the approximate distance of the source using the received signal strength. This allows the collision avoidance algorithm to react only to agents within a certain circle of radius ρ (the "repulsion radius"). ρ effectively is an agent's collision avoidance range and represents the distance an agent must keep between itself and its neighbors to leave sufficient space to turn. Therefore, ρ is dependent on the agent's *turning radius r*.

For the control algorithm, we define:

$$I_{y,i} = \sum_{j=1}^{n} A_y / (\| \underline{x_j} - \underline{x_i} \|_2^2) \tag{1}$$

where $I_{y,i}$ is a measure proportional to the received power of beacon type y at agent i at location x_i with $y \in \{col, tar\}$, and A_y is the transmit power of type y beacons. (There are a total of n agents, and all beacons of the same type are assumed to have the same power). Using the directional sensitivity of two side-looking directional antennas, we can find the following signal intensity for left and right looking antennas of each of the two modalities:

$$R_{y,i} = \sum_{j \in \Gamma_y} A_y f(\underline{x_j} - \underline{x_i}, \underline{\eta_i}) / (\| \underline{x_j} - \underline{x_i} \|_2^2) \tag{2}$$

$$L_{y,i} = \sum_{j \in \Gamma_y} A_y f(\underline{x_j} - \underline{x_i}, -\underline{\eta_i}) / (\| \underline{x_j} - \underline{x_i} \|_2^2) \tag{3}$$

with $\Gamma_{col} = \{j | \| \underline{x_j} - \underline{x_i} \|_2 < \rho\}$, $\Gamma_{tar} = \{1, \cdots, n\}$, $\underline{\eta_i}$ being the right normal vector to the speed vector of agent i in the plane of operation (i.e., either on the ground or in the flight plane), and $f(x, \eta)$ being the directional sensitivity function of the antenna, where x is the vector from receiver to source and $\underline{\eta}$ is the direction of highest sensitivity of the antenna. In the case of $y = col$, the summation for the left and right antenna signal intensity L_i and R_i respectively are taken only over those agents j that satisfy $\| \underline{x_j} - \underline{x_i} \|_2 < \rho$.

Algorithm 1 Basic navigation control [1]

```
if S_col,i > 0 then
   if D_col,i > 0 then
      turn right
   else
      turn left
   end if
else if S_tar,i > threshold then
   if D_tar,i > 0 then
      turn left
   else
      turn right
   end if
else
   fly straight
end if
```

The decision for the turn direction requires two directional antennas on each side of the agent facing in opposite directions ($\underline{\eta}$, and $-\underline{\eta}$), perpendicular to the agent speed vector. Since the turning radius r of the agent is assumed to be independent of the direction (left and right), a simple intensity comparison between left and right directional antenna will allow to derive the new heading of the agents, which is either "turn left" or "turn right". Define the intensity sum and difference between the antenna pairs as: $L_{y,i}+R_{y,i}=S_{y,i}$, $L_{y,i}-R_{y,i}=D_{y,i}$, $y\in\{col,tar\}, i=1,\cdots,n$, where $S_{y,i}$ and $D_{y,i}$ denote sum and difference of left and right antenna signal strength of modality y at agent i. This basic navigation control algorithm is given in Algorithm 1.

III. Modeling Sensor Evidence

DS theory [8] provides a robust approach towards representing data imperfections including inaccuracies, uncertainties and ambiguities [9]. Moreover, it is straightforward to represent multi-modal sensor data using DS theory [10], making it a better candidate for this context. The strategy we present here is based on DS theory representing multi-modal sensor data as belief theoretic evidence, and an extension to it proposed by the authors to accommodate evidence updating in heterogeneous sensor environments [10].

A. Dempster-Shafer Theory

We denote the total set of mutually exclusive and exhaustive propositions a node may discern via $\Theta=\{\theta_1,\ldots,\theta_n\}$, viz., Θ is the corresponding *frame of discernment (FOD)* signifying the scope of 'expertise'. A proposition θ_i represents the lowest level of discernible information. $|\Theta|$ denotes the cardinality of set Θ, and 2^{Θ} denotes its power set. Propositions of interest are then of the form $A\subseteq\Theta$ generated from the power set 2^{Θ} of Θ. We use $A-B$, $A,B\subseteq\Theta$, to denote all propositions in A after removal of those propositions that may imply B, i.e., $A-B=\{\theta:\theta\in A,\ \theta\notin B\}$; The support for any proposition A is provided via a *mass assignment*:

Definition 1: The mapping $m:2^{\Theta}\mapsto[0,1]$ is a *basic belief assignment (BBA)* for the FOD Θ iff (i) $m(\emptyset)=0$; and (ii) $\sum_{A\subseteq\Theta}m(A)=1$.

The set of propositions $\mathscr{F}(\Theta)$ that possesses nonzero masses forms the *focal elements* of Θ; The triple $\{\Theta,\mathscr{F},m\}$ is referred to as the *body of evidence (BOE)*.

Definition 2: Given a BOE $\{\Theta,\mathscr{F},m\}$ and $A\subseteq\Theta$, define (i) *belief* as $\mathrm{Bel}:2^{\Theta}\mapsto[0,1]$ where $\mathrm{Bel}(A)=\sum_{B\subseteq A}m(B)$; (ii) *plausibility* as $\mathrm{Pl}:2^{\Theta}\mapsto[0,1]$ where $\mathrm{Pl}(A)=\sum_{B\cap A\neq\emptyset}m(B)$; and (iii) *Uncertainty* associated with A as the interval $\mathrm{Un}(A)=[\mathrm{Bel}(A),\mathrm{Pl}(A)]$.

The mass $m(A)$ measures the support to proposition A only, while the belief assigned to A measures the supports for all proper subsets of A,i.e., the total support that can move into A without any ambiguity. $Pl(A)$ represent the extent to which one finds A plausible. When the set of focal elements $\mathscr{F}$ contains singletons only, the mass, belief and plausibility functions all reduce to probability. By assigning masses for composite propositions, it is quite straightforward to model uncertainties and ambiguities using DS theory when complete sensor models or 'a priori' probabilities are not readily available in a multi-modal sensor environment. Moreover, It is capable of more easily accommodating the qualitative aspects of information during knowledge representation and refinement under uncertainties [11].

B. Evidence Updating

In DS theory, the *Dempster's combination function* allows one to find a new BOE by combining the evidence generated by several BOEs spanning the *same* FOD [8]. The fact that the two BOEs being combined are required to be from identical FODs constitutes the main drawback associated with this evidence combination function. Several other approaches are available to handle the combination of evidence from non-identical FODs [10], [12].

The research in [10] presents a method to handle such non-identical FODs while considering sensor reliability as well as inertia and integrity of available evidence in a heterogeneous sensor environment. This approach has been further extended to 'evidence filtering' [13] where the 'frequency' characteristics of various multi-modal events could be directly studied with the temporal ordering of evidence. These features could be highly useful in the current context, and also in possible future extensions of the navigation scheme presented here to detect more complex spatio-temporal signal signatures. Hence, we use the strategy in [10] for evidence updating inside each swarm agent over time. For simplicity, let us consider the homogeneous case of the strategy presented in [10]:

Definition 3: [10] Given the BOEs $\{\Theta,\mathscr{F}_1,m_1\}$ and $\{\Theta,\mathscr{F}_2,m_2\}$, and a given $A\in\mathscr{F}_2$. The *updated belief* $Bel_{k+1}:2^{\Theta}\mapsto[0,1]$ and *updated plausibility* $Pl_{k+1}:2^{\Theta}\mapsto[0,1]$ of an arbitrary proposition $B\subseteq\Theta$ are

$$\begin{aligned}\mathrm{Bel}(B)_1(k+1)&=\alpha_k\cdot\mathrm{Bel}(B)_1(k)+\beta_k\cdot\mathrm{Bel}(B|A)_2(k)\\ \mathrm{Pl}(B)_1(k+1)&=\alpha_k\cdot\mathrm{Pl}(B)_1(k)+\beta_k\cdot\mathrm{Pl}(B|A)_2(k)\end{aligned}\tag{4}$$

where $\alpha_k\geq0,\beta_k\geq0$ and $\alpha_k+\beta_k=1$. The constraints on positivity and sum are needed to ensure that the updated beliefs constitute a valid belief function. The conditional in (4) is the Fagin-Halpern conditional in [14] which can be considered a more natural extension of the Bayesian conditional notions. It is possible to have different conditioning events A. In fact, proper choice of the conditioning event A may often improve

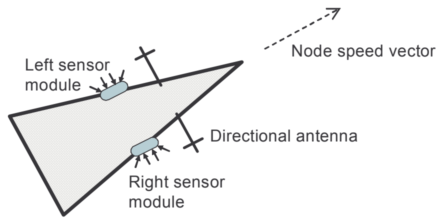


Fig. 2. Swarm agent (hovercraft) with directional, multi-modal sensor modules

the performance of the final decision making process based on the updated evidence. In the evidence updating strategy in (4), the term $\mathrm{Bel}(B|A)_2(k)$ captures the portion of the incoming evidence while $\mathrm{Bel}(B)_1(k)$ captures the already available evidence. The updated belief is given by $\mathrm{Bel}(B)_1(k+1)$ and similar notions hold for the plausibility.

IV. Navigation Algorithm for Signature Triggered Beacons

In this section, we describe the incorporation of a signature detection strategy and the implementation of a signature based triggering mechanism to replace the threshold triggered beacon activation mechanism described in Section II. The modified navigational behavior of agents is given in Algorithm 2 described below. Note that the first portion of this Algorithm is derived from Algorithm 1 [1], and it has priority over the evidence based navigational decisions, in order to avoid collisions using *col* beacons and to respond to any *tar* beacons present. Otherwise, the navigational decisions are made using the latter portion of the algorithm based on belief updates with multi-modal sensor readings.

Let us consider the complete trajectory of a single swarm agent. We can identify three phases in its navigational behavior.

1. *Pre-detection phase:* No signal modalities detected so far, node behavior is completely governed by beacons *col* and *tar*.
2. *Signature detection phase:* Navigational behavior affected by updated evidence using sensor readings.
3. *Post-detection phase:* Emit the *tar* beacon to attract other agents to the area for further scanning.

Our contribution is mainly for the phase 2 above. We now describe how the navigational decisions are made during this signature detection phase:

Suppose the signature scanned for is characterized by modalities $m \in \{1,\ldots,N\}$. All mobile nodes (swarm agents) are equipped with sensors which can identify each of these N different modalities. Two sensors are used for each signal modality to be sensed. These sensors are directional, fitted in opposite directions in the left and right sides of the node, perpendicular to its speed vector as shown in Figure 2. Each node maintains a BOE over the FOD $\Theta = \{\theta_1,\ldots,\theta_N\}$ where each singleton proposition θ_m correspond to sensor modality m. Each mobile node samples its sensor signals (left and right, for all modalities) and updates its BOE accordingly, at regular sampling intervals synchronized with the clock signal

Algorithm 2 Evidence based navigation

```
update beliefs
if S_{col,i} > 0 then
   if D_{col,i} > 0 then
      turn right
   else
      turn left
   end if
else if S_{tar,i} > threshold then
   if D_{tar,i} > 0 then
      turn left
   else
      turn right
   end if
else if Bel_i(θ_m) > T_{1,m} for any m ∈ {1,...,N} then
   m_0 = arg max Bel(θ_m)                {modality with nav priority}
   if m_0 = previous m_0 then
      r_i = r_i + Δ                      {increase turn radius}
   else
      r_i = R                            {reset turn radius}
   end if
   save m_0
   if D_{m_0,i} > 0 then
      turn right
   else
      turn left
   end if
else
   fly straight
end if
if Bel_i(θ_m) > T_{2,m} ∀ m ∈ {1,...,N} then
   trigger attractive beacon tar
end if
```

used for the algorithm in [1]. The belief towards modality m in mobile node i at k-th sampling instance is updated based on (4) as,

$$\mathrm{Bel}_i(\theta_m)_1(k+1) = \alpha \cdot \mathrm{Bel}_i(\theta_m)_1(k) + \beta \cdot \mathrm{Bel}_i(\theta_m|A)_2(k) \quad (5)$$

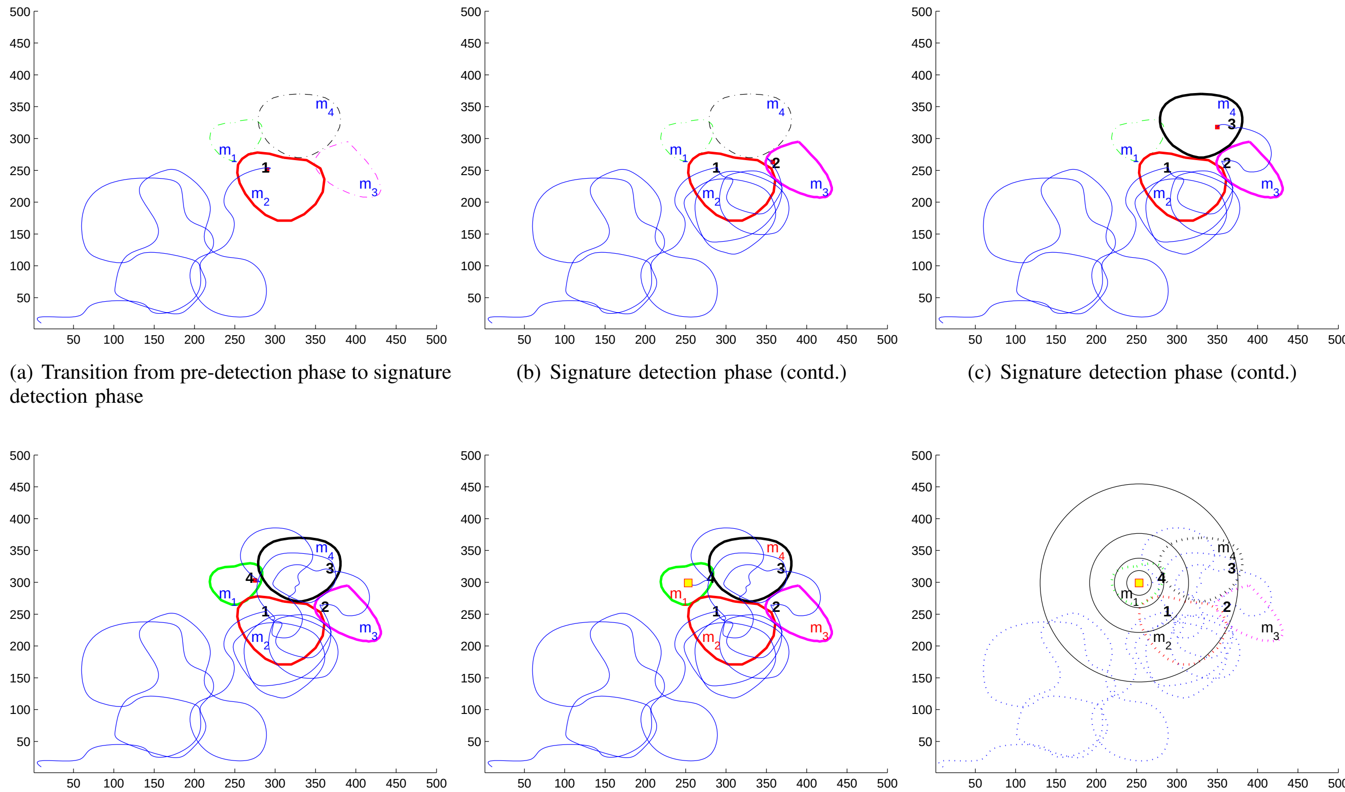
where $A \subseteq \Theta_2$ is a properly chosen conditioning event. The term $\mathrm{Bel}_i(\theta_m)_1(k)$ represents the current belief towards modality θ_m and the conditional belief term $\mathrm{Bel}_i(\theta_m|\Theta)_2(k)$ represents the new evidence derived using the current sensor signals of modality m. For the simple choice of $A = \Theta_2$, (5) becomes a linear combination of the available and incoming evidence [10]. The coefficients α, β determine the weight given to the inertia of the currently available evidence on modality m, and is an important design parameter affecting the behavior of the swarm towards detection of the signature sought.

It is important to note that the computation in (5) can be implemented in mobile nodes using a simple first order process with minimal analog hardware using an R-C realization, making this an attractive option for expendable, low-cost swarm platforms. While keeping the control functions based on the *col* and *tar* beacons intact, the Algorithm 1 is modified as follows:

(i) If the belief towards **at least one** of the modalities m were detected to be above a pre-specified lower threshold $T_{1,m}$, i.e.,

$$\mathrm{Bel}_i(\theta_m) > T_{1,m} \text{ for any } m \in \{1,\ldots,N\} \quad (6)$$

then the modality m_0 with *navigation priority* is deter-



(a) Transition from pre-detection phase to signature detection phase

(b) Signature detection phase (contd.)

(c) Signature detection phase (contd.)

(d) Signature detection phase (contd.)

(e) End of signature detection phase

(f) post-detection phase

Fig. 3. flight trajectory snapshot of an individual node

mined as

$$m_0 = \arg\max_m \quad \text{Bel}_i(\theta_m). \tag{7}$$

(ii) If m_0 is equal to the previously detected m_0 indicating continuous navigation inside a region of modality m_0, increment the turn radius r by a quantity Δ. Otherwise, the mobile node has moved to a region of a different modality and hence reset the turn radius r to its original value R. Save current m_0 for later use.

(iii) Compute the difference measure $D_{m_0,i}$ for sensor modality m_0 as,

$$D_{m_0,i} = L_{m_0,i} - R_{m_0,i} \tag{8}$$

where $L_{m_0,i}$ and $R_{m_0,i}$ are the current sensor signal strengths for the left and right sensors of modality m_0 respectively. The turn direction is determined according to the sign of $D_{m_0,i}$ as in Algorithm 2.

(iv) If the beliefs of **all** modalities characterizing the signature sought are above their upper thresholds $T_{2,m}$, i.e.,

$$\text{Bel}_i(\theta_m) > T_{2,m} \,\forall\, m \in \{1,\ldots,N\} \tag{9}$$

then emit the target attraction beacon *tar*.

The lower threshold $T_{1,m}$ in above step (i) ensures that the increase in turn radius occurs only after the mobile node has entered a region with sufficiently high intensity level of modality m. This along with the functionality in above step (ii) ensures that the mobile node will attempt to cover the region with detection of modality m in a spiral-shaped navigation path of increasing radius, starting close to the center of the region. The goal is to explore the vicinity of this region completely, and seek other modalities.

During successive scanning, when the mobile node moves into a new region with a different modality of navigational priority, the turn radius is reset to its original value R. Next, the node attempts to scan this new region using a new outward spiral path starting from its center. This process is further illustrated with the simulations in Section V. These maneuvers are continued until all modalities are detected beyond a set of upper thresholds $T_{2,m}$ triggering the attractive beacon *tar*.

V. Simulation Results

The above evidence-based navigation algorithm is applied to a swarm of mobile sensor nodes searching for a unique signature exhibiting certain properties in four adjacent areas. These properties correspond to modalities m_k, $k \in \{1,2,3,4\}$, and their dispersion areas are shown in Figure 3(a). Consider the trajectory of a single mobile node scanning the area. Until it reaches the region with modality m_2, the navigation is based on the collision avoidance beacons *col* of other nodes. Assume no target attraction beacon *tar* is active yet. Accordingly, the initial portion of the path shown in Figure 3(a) shows the pre-detection phase of the node considered.

Once it reaches the area with modality m_2 as marked by time instance 1 in Figure 3(a), the node enters the signature detection phase. The sensors for modality m_2 detects the

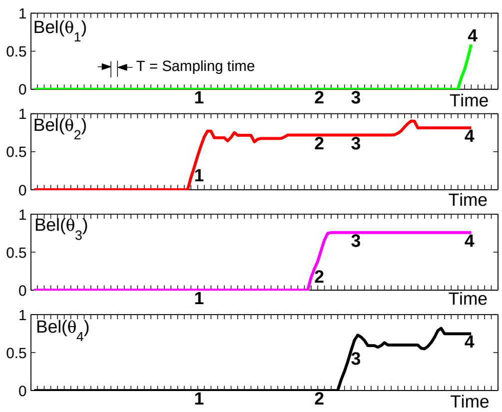


Fig. 4. Belief variation over the trajectory of mobile node

presence of it and as a result, the beliefs are updated using (5). Here we used the simple choice of conditioning event $A = \Theta_2$ and the variation of updated belief over time is shown in Figure 4. Thereafter, the mobile node assumes an outward spiral navigation path around the region of modality m_2 as shown in Figure 3(b). Note that the quality of the detection of a particular modality vary over this region and deteriorates from the center towards the boundaries of these areas. The detection deep inside these regions is better than on the periphery.

Figures 3(b) - 3(d) shows the detection of regions with modalities m_3, m_4 and m_1 respectively, during the signature detection phase. The thresholds $T_{1,m} = 0.1$, $T_{2,m} = 0.6$ and $\alpha = 0.7$ were used during the simulation. Figures 3(e) indicates the completion of the signature detection. Figure 3(f) shows the node in its post-detection phase activating the *tar* beacon to attract other agents to the region for further discovery.

Note that in this simulation, we only displayed all three navigational phases of one single agent of the swarm to illustrate the evidence based updating strategy. However, the agent behavior is continuously affected by the *col* and *tar* beacons emitted by other nodes, and they always have precedence over the modified evidence-based navigation rules as mentioned before.

VI. Concluding Remarks

An evidence based navigation scheme for the detection of a multi-modal signal signature using swarms of mobile sensor nodes is presented. It offers a novel method to detect and track unique signatures characterized by a mix of signal modalities in a local area. The information gathered by sensors are modeled as evidence, based on DS theory. Temporally ordered evidence is used to make navigational decisions and trigger an attractive beacon, to draw other nodes towards the signal signature for further exploration. This method can be important in situations where a target area is described by classes of interesting signal signatures with varying intensity in space or time. In many cases, these signatures cannot be characterized well by the presence or absence of a single signal modality.

Future work include the extension of the algorithm to detect more complex, spatio-temporally dependent signatures. The possibility of incorporating evidence filters [13] for this purpose also need to be explored. In the simulation example presented, we considered individual signal modalities (corresponding to singleton beliefs in the agent BOE) within each region of interest. In real world applications, it would be important to have a detection capability looking for classes of signals denoted by composite propositions in an agent's BOE. Studying the proper choice of conditioning event A in (4) may prove to be useful towards developing this capability.

Introducing a small degree of random switching between left and right directions during the navigation over the region of signature may further increase the robustness of the search process, offering faster detection and better coverage of area. The algorithm will be tested in a real world scenario using a swarm of hovercrafts with on-board multi-modal sensors in the future.

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