# Bio-inspired Practicalities: Collective Behaviour using Passive Neighbourhood Sensing

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## ABSTRACT

Implementing collective behaviour in cooperative multi-agent systems requires several practical constraints to be addressed. In some environments, communication bandwidth is a critical constraint which may compromise the intended cooperative behaviour. This paper introduces a bio-inspired model which invokes collective behaviour in a multi-agent system using passive sensing without any explicit inter-agent communication. An agent looks for the majority of its neighbours either in its left or its right half space using two sensors. For a source localization problem, we compare performance of the proposed model using passive sensing against the well known school-of-fish collective behaviour models using ideal explicit inter-agent communication. For different cue strengths and neighbourhood radii, our results show that the proposed strategy boosts higher levels of group cohesion to make up for the information loss and in certain conditions performs better than the other collective behaviour models.

## Categories and Subject Descriptors

I.2.9 [**Robotics**]: Autonomous Vehicles; I.2.11 [**Distributed Artificial Intelligence**]: Multiagent systems

## Keywords

Biologically-inspired approaches and methods, Collective intelligence, Distributed problem solving, Emergent behavior

## 1. INTRODUCTION

With time, multi-agent systems have become a focal point in various fields of applied engineering research [54, 47, 52, 60] where researchers have formulated multi-agent strategies to solve different engineering problems [16, 46, 70]. A large contribution to the literature on physical multi-agent systems is biologically inspired [23, 41, 29, 26] from the collective behaviour in nature [64, 28]. In the domain of source localization, there are significant number of bio-inspired approaches and methods in the literature [20, 23, 40, 59]. Such implementations, either require explicit inter-agent communication, i.e., a deliberate act of invoking a signal transmission [45, 65] or use passive sensing of the environment or neighbours [51, 63].

In a nutshell, any cooperative source localization task requires some kind of information transfer which depends on the modality of a communication infrastructure, i.e., explicit or implicit [4]. Performance of explicit communication based strategies suffer substantially in the environments with severely limited communication bandwidth and delays, e.g., undersea environments [19, 17]. In such environments, having an implicit communication based strategy allows the multi-agent system to operate cooperatively potentially without a complete breakdown. However, implicit communication based strategies that appear in the literature are inspired from ants' pheromone sensing where an agent looks for other agents' passage trails in the environment [4, 51, 63]. In many practical scenarios, whether on land or underwater, explicitly depositing or implicitly leaving a pheromone-like trail may not be desirable or even possible.

We present a control strategy that invokes collective behaviour in multi-agent systems using only two passive sensors per agent. Fish schools or shoals are optimally evolved systems by the process of natural selection and find food [55] or acoustic [49, 56] sources benefitting from their collective behaviour. An ideal but a challenging approach is to translate this optimally evolved biological model into a practical control strategy for autonomous multi-agent systems. We discuss the practicalities of such a translation in Section 2 and present the passive sensing model in Section 3. In the proposed strategy, an agent uses the two sensors to look for where the *majority* of its neighbours are positioned, either in its left or right half space. Though similar notions pertaining to the dual sensors [11] or the neighbour majority [12] exist in the literature, the proposed strategy is novel in the way it integrates the two ideas to offer a practical collective behaviour based distributed control approach. We present the simulation setup in Section 4 and compare the performance of the proposed model against the biological models aided by explicit communication in Section 5. We finally conclude in Section 6 summarizing the important findings of this paper and sharing some thoughts pertaining to the future work.

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**Appears in:** *Proceedings of the 14th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2015), Bordini, Elkind, Weiss, Yolum (eds.), May 4–8, 2015, Istanbul, Turkey.*

# 2. BIO-INSPIRED PRACTICALITIES

## 2.1 Biological Collective Behaviour Models

In a school of fish, the collective behaviour is believed to emerge from an individual's interaction with its neighbours [42, 32]. Many years of research [18, 2, 34] has classified three major rules that result in the collective behaviours, i.e., the long-range attraction, the short-range repulsion and the neighbour alignment. An individual fish is attracted towards its neighbour unless it gets too close, in which case repulsion takes over attraction – a phenomenon jointly known as the long-range attraction and short-range repulsion. Current literature on animal collective behaviour shows a lack of consensus on whether these animal interactions are based on metric/zonal interactions [58, 18, 31, 34] or topological interactions [7, 24, 10]. By metric interaction, one assumes the interaction of the focal animal with its neighbours within a fixed radius. There are three distinct zones defined within the fixed radius of interaction as shown in Fig. 1. For a distance, $r \in \mathbb{R}^+$ (m), away from the fish, there exists a repulsion zone such that $0 < r \leq r_\mathrm{r}$, an orientation zone such that $r_\mathrm{r} < r \leq r_\mathrm{o}$ and an attraction zone such that $r_\mathrm{o} < r \leq r_\mathrm{a}$. By topological interaction, one assumes that the focal animal interacts with a fixed number of nearest neighbours but these models are more restricted in explaining the collective behaviour in some flocks of birds and their generic application is rather debatable [9, 42].

For metric/zonal interaction, there are numerous models having some very subtle differences between them but many of them fit the experimental data quite well. A very simple model [18, 9] is based on the unit vector information of the neighbour positions. For example, in case the focal fish, $i$, with position, $\mathbf{x}_i(t)$, at time, $t$, detects any neighbour(s), $j$, inside its repulsion zone, i.e., the inter-agent distance, $r_{ij}(t) = |\mathbf{x}_j(t) - \mathbf{x}_i(t)| \leq r_\mathrm{r}$, it assumes heading according to the following direction vector

$$\mathbf{d}_{\mathrm{r}_i}(t + \tau_\mathrm{r}) = -\sum_{j \neq i}^{n_\mathrm{r}(t)} \frac{\mathbf{x}_j(t) - \mathbf{x}_i(t)}{r_{ij}(t)} \tag{1}$$

where $\tau_\mathrm{r}$ is the sampling time and $n_\mathrm{r}(t)$ are the number of neighbours in the repulsion zone. Similarly for any neighbour(s), $j$, in the attraction zone such that $r_\mathrm{o} < r_{ij}(t) \leq r_\mathrm{a}$, the focal fish, $i$, would assume heading as

$$\mathbf{d}_{\mathrm{a}_i}(t + \tau) = \sum_{j \neq i}^{n_\mathrm{a}(t)} \frac{\mathbf{x}_j(t) - \mathbf{x}_i(t)}{r_{ij}(t)} \tag{2}$$

where $\tau$ is the sampling time and $n_\mathrm{a}$ are the total number of neighbours in the attraction zone. The repulsion zone holds the highest priority and in case a neighbour is found therein, other behaviours are suspended.

There are other collective behaviour models which build more directly on the significance of the centroid of the school's mass [5, 25, 30, 53]. Some of these models assume a somewhat unrealistic notion that a focal fish has the knowledge of the global centroid and tries to bias itself towards that center. Nevertheless, there are models that only assume knowledge of the centroid of neighbour positions within a fixed radius [56, 58, 50]. In fact, we can write a very simple centroid model by slightly modifying (1) and (2) such as

$$\mathbf{d}_{\mathrm{r}_i}(t + \tau_\mathrm{r}) = -\sum_{j \neq i}^{n_\mathrm{r}(t)} (\mathbf{x}_j(t) - \mathbf{x}_i(t)) \tag{3}$$

and

$$\mathbf{d}_{\mathrm{a}_i}(t + \tau) = \sum_{j \neq i}^{n_\mathrm{a}(t)} (\mathbf{x}_j(t) - \mathbf{x}_i(t)) \tag{4}$$

respectively. By limiting the $r_\mathrm{a}$ in the centroid model, we can mimic knowledge of the local centroid and by increasing it to a very large number, we can mimic knowledge of the global centroid.

The orientation models serve the purpose of mimicking the *polarization* of a school, i.e., the mean of the angle deviation of each fish to the mean swimming direction of the school [34]. The long-range attraction and short-range repulsion model without the orientation model accounts well for the *expanse* of a school, i.e., the mean distance of all the fish from the school's centroid, but not so much for the polarization [42]. It is also known that the phenomenon of neighbour alignment in the orientation zone is dependent on the radial neighbour density. For example, a low density would result in a disordered orientation and only for a certain threshold of density, order emerges and increases thereafter as a function of group size [69, 21]. Such a transition from disorder to order (alignment) is seen in a group of locusts [13] where for small populations, there is no significant alignment among individuals. Similar transitions are observed in a school of fish [8]. These observations hint towards the possibility of alignment being an emergent property that is a consequence of long-range attraction and short-range repulsion phenomenon in a high density group. Also, from the perspective of a source localization problem, there is a high chance that alignment may result as an implicit consequence of following a certain cue. For example, a recent study has shown that alignment emerges from the long-range attraction and short-range repulsion phenomenon when agent speeds are varied as a function of instantaneous cue intensities [38]. Since this paper focuses on a team with small number of agents (1 – 20) and a source localization problem, we discount the orientation model in favour of keeping focus only on the role of the long-range attraction and the short-range repulsion behaviours.

To discount the orientation zone we set $r_\mathrm{o} = r_\mathrm{r}$ which applies to (2) and (4). For comparison of the biological models with the passive sensing model, we refer to the unit vector model as the UV model and the centroid model as the C model in the following text. Hence, UV model generates direction vectors for an autonomous agent based on (1) and (2) and C model generates direction vectors based on (3) and (4).

## 2.2 Practicalities of the Long-range Attraction

Long-range attraction is the key behaviour that contributes towards the cohesion and compactness of a group. It is interesting to investigate the advantages of having an attraction behaviour in multi-agent systems for some real-world problem. It has been shown that the long-range attraction behaviour without aid of any other collective behaviours (repulsion or orientation) can contribute towards increasing the efficiency of a source localization problem [59]. However, the implementation cost of behaviours given by (2) and (4) is in

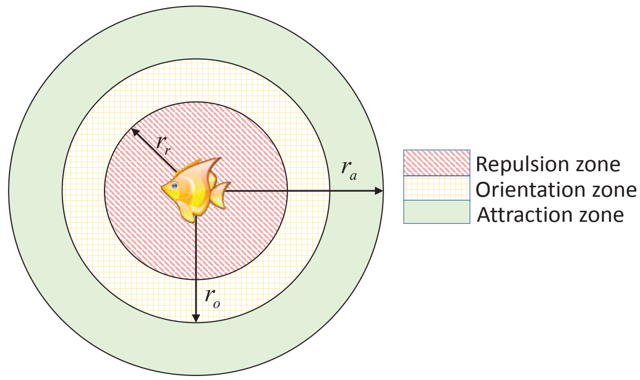



Figure 1: Zonal model of fish interaction.

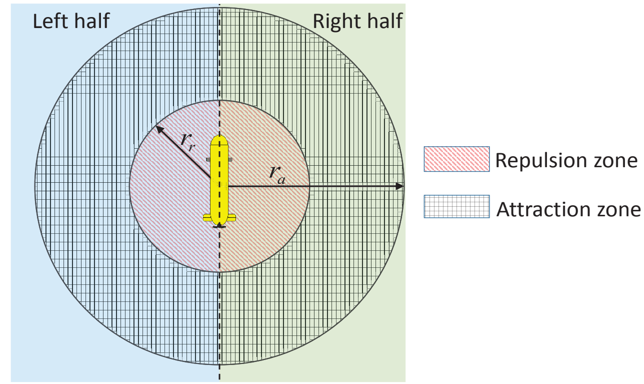



Figure 2: Passive sensing zonal model for detecting majority of neighbours either in left or right half space.

terms of an agent acquiring its own reliable position estimate and to establish communication with other agents to exchange the position information. Acquiring a reliable position estimate and/or communication with acceptable delays and bandwidth in certain environments is a hard and an expensive problem to solve [39, 62].

Having small interaction neighbourhoods may alleviate the communication issues to some extent [6, 36]. However from the perspective of a source localization problem, having a small neighbourhood may consequentially require a very large team of agents [55]. For example, a small team with agents having small neighbourhood radii will be potentially sampling a strong spatially-correlated cue which will have detrimental effects on its collective decision making [37]. Fish are known to have small neighbourhoods but some schools of fish undertaking distant migration are composed of several million individuals connected through small neighbourhoods over several kilometers [48, 43]. It is highly unlikely in the present times to build a massive swarm of autonomous agents with sufficient mission endurance to solve a real-world problem. Given a small number of agents (3 – 20), we show in Section 5 that C and UV models require a large neighbourhood (in hundreds of meters) for localizing an acoustic source 1000 m away.

## 2.3 Practicalities of the Short-range Repulsion

Repulsion allows more volume to a school allowing it to span more space. Also, increasing $r_\mathrm{r}$ results in decreasing cohesion in a school [34]. There is also a difference of opinion on the effect of repulsion on the overall schooling, e.g., some studies report that removing the repulsion zone causes school disintegration [2, 3], whereas some report that removal of the repulsion zone has insignificant effect on schooling [33, 34, 35]. Nevertheless, it is interesting to investigate the effect of the short-range repulsion on a school-of-fish or a team of autonomous agents in a source localization problem.

Short-range repulsion suffers from the same issues as discussed in the preceding section for the long-range attraction. Models defined in (1) and (3) also require the focal agent to acquire the position information of all the neighbouring agents. However, the short-range repulsion allows sophisticated multi-agent systems such as land robots, Unmanned Aerial Vehicles (UAVs) or AUVs to avoid collisions with their peers during a cooperative mission. From the perspective of an agent safety, collision avoidance control is indispensable in most physical multi-agent setups.

# 3. THE PASSIVE SENSING (PS) MODEL

As discussed in the preceding section, C and UV models require explicit communication of inter-agent position information. Our focus is an alternate collective behaviour model that builds on the biological counterparts but only requires passive sensing to achieve similar characteristics and performance. We assume that each agent is equipped with two passive sensors, one on its right side and one on its left side. This effectively partitions the two-dimensional sensing world of an agent as shown in Fig. 2 into right and left half plane. The passive sensing model requires an agent to have the following information

1. Where is the majority of neighbours in my attraction zone? Either to my right or to my left?

2. Are there any neighbours inside the repulsion zone? If so, what is the *estimated* distance to the closest one and which half is it located in?

Based on this information an agent exercises short-range repulsion and long-range attraction behaviours.

## 3.1 Collective behaviours of the PS Model

Short-range repulsion operates at the highest priority level. In case an agent detects a neighbour within its repulsion zone, it starts an evasive action and ignores any other behaviours such as going towards the goal or towards the neighbours etc. The evasion rules for an agent are:

1. If there are any number of neighbours inside the repulsion zone, estimate the distance to the nearest neighbour.

2. Determine the half (right or left) in which the nearest neighbour is located.

3. Initiate a turn in the opposite half (left or right) with a turning rate dependent on the estimated nearest neighbour distance.

The turning rate as a function of the distance between the focal agent, $i$, and the nearest neighbour, $j$, within the repulsion zone is given as

$$\dot{\theta}_{\mathrm{r}_i}(t+\tau_{\mathrm{r}}) = \begin{cases} \dot{\theta}_{\max}\left(\frac{r_{\mathrm{r}}-\hat{r}_{i,j}(t)}{r_{\mathrm{r}}-r_{\min}}\right) & \text{if } r_{\min} < \hat{r}_{i,j}(t) \leq r_{\mathrm{r}} \\ \dot{\theta}_{\max} & \text{if } \hat{r}_{i,j}(t) \leq r_{\min} \end{cases} \quad (5)$$

where $\tau_{\mathrm{r}}$ is the sampling time of the repulsion behaviour, $\hat{r}_{i,j}(t)$ is the estimated distance between the focal agent and the nearest neighbour through the sensor data (more on this in Section 3.2) and $r_{\min}$ is the minimum distance between the focal agent and the nearest neighbour where the focal agent starts turning with the maximum possible rate. Also, $r_{\min}$ needs to be greater than $2s\tau_r + l$ for an agent to detect all the potential collisions where $s$ and $l$ are the agent speed and length respectively. Then the focal agent, $i$, assumes heading according to the following direction vector

$$\mathbf{d}_{\mathrm{r}_i}(t+\tau_{\mathrm{r}}) = \mathbf{\Delta d}_{\mathrm{r}_i}(t+\tau_{\mathrm{r}}) + \mathbf{d}_i(t) \quad (6)$$

where $\mathbf{\Delta d}_{\mathrm{r}_i}(t+\tau_{\mathrm{r}}) = 1\angle\tau_{\mathrm{r}} \cdot \dot{\theta}_{\mathrm{r}_i}(t+\tau_{\mathrm{r}})$ and $\mathbf{d}_i(t)$ being the instantaneous unit directional vector of agent $i$.

For the long-range attraction behaviour, at every $\tau$ seconds, an agent calculates its desired heading towards the majority of its neighbours by detecting the majority either in its left or right half as

$$\mathbf{d}_{\mathrm{a}_i}(t+\tau) = \begin{cases} R^{+}_{\phi}\mathbf{d}_{\mathrm{w}_i}(t) & \text{if more neighbours on left} \\ R^{-}_{\phi}\mathbf{d}_{\mathrm{w}_i}(t) & \text{if more neighbours on right} \\ \mathbf{d}_{\mathrm{w}_i}(t) & \text{otherwise} \end{cases} \quad (7)$$

where $R^{+}_{\phi}, R^{-}_{\phi}$ are the counter clockwise and the clockwise rotation matrices for an angle of $\phi = 90^\circ$ and $\mathbf{d}_{\mathrm{w}_i}(t)$ is the previous weighted direction (see Section 4 for details on computation of the weighted direction).

## 3.2 Practicalities of the PS model

Here we provide some examples of using the dual sensor topology from the perspective of practical implementation. A very simple scenario is using two microphones or hydrophones per agent where the focal agent can *listen* for the presence of its neighbours. In most of the situations the drive or propulsion systems of land robots, UAVs or AUVs make a significant amount of noise which can be sensed easily by the focal agent within some local neighbourhood. Using the time-of-arrival analysis on the sensors' data can help the focal agent detect where the majority of neighbours is located. In fact in harsh environments, such as undersea environments, where communication bandwidth is severely limited, low frequency sound signals like the thruster noise can travel several hundreds of meters [22, 67, 15]. The thruster noise of a typical AUV or a ROV is in the range of 120 dB to 160 dB re 1 $\mu$Pa at 1 m [27, 14]. AUVs can also be mounted with locator beacons which emit an acoustic pulse at a fixed rate in time. For example, a 20 kHz pinger with a source level of 180 dB re 1 $\mu$Pa at 1 m can be heard over several kilometers undersea. In environments where light can travel, e.g., clear waters, the two sensors can simply be light detectors. For example, in the case of CoCoRo project, the researchers use small AUVs which can emit light [65]. Comparing the mean value of light intensity sensed by each sensor over some time window can give a good estimate of where the majority of the neighbours are. Cameras can also be an option as two passive sensors in many environments where robots can detect the neighbour majority using simple image processing techniques.

Where an estimate of the neighbour majority completely defines the long-range attraction behaviour, the short-range repulsion behaviour requires the estimated distance from the nearest neighbour in (5). In the PS model, the neighbour itself is a source. Given an agent has some prior knowledge of the source intensity and its propagation model, it can obtain a good estimate of the distance in close proximity to a source. This is especially true for sources which follow the inverse square law, i.e., the intensity is inversely proportional to the distance squared. Since the repulsion radius is generally small, the assumption pertaining to the knowledge of the estimated nearest neighbour distance is practically valid.

# 4. SIMULATION SETUP

Let us first define the source localization problem considered in this paper. We assume an acoustic point-source located at the origin of the search plane. Arrival time is defined as the time taken by a specific agent to enter a circular success zone around the source and not diverge from the success zone following its initial entry. The radius of the success zone, $r_{\mathrm{s}}$ is set to 50 m. For sensing the intensity of the source, we use a sound propagation model with spherical spreading suitable for deep underwater environments [66]. For the source, we assume a sound pressure level of 180 dB re 1 $\mu$Pa at 1 m away in the bandwidth of interest. For the ambient noise, we assume noise levels of either 84 dB re 1 $\mu$Pa or 118 dB re 1 $\mu$Pa for comparative performance analysis of the collective behaviours in different Signal to Noise Ratio (SNR) conditions. Both the noise levels at 84 dB re 1 $\mu$Pa and 118 dB re 1 $\mu$Pa correspond to the deep sea noise and the shallow water noise respectively in a real-world scenario [22]. The source level correspond to the sound levels of many commercially available underwater locator beacons. We initialize a team of $N$ AUVs, each with a random pose within a square region having an area of $20 \times 20$ m$^2$ and its center located 1000 m away from the acoustic source.

To bias an agent towards the source, we choose an individual behaviour that has the ability of helping an agent localize a source without the aid of collective behaviours [59]. According to the source bias model, an agent updates its direction as follows

$$\mathbf{d}_{\mathrm{s}_i}(t+\tau) = \begin{cases} \mathbf{d}_{\mathrm{w}_i}(t) & \text{if } I(t+\tau) \geq I(t) \\ R^{+}_{\theta}\mathbf{d}_{\mathrm{w}_i}(t) & \text{if } I(t+\tau) < I(t) \end{cases} \quad (8)$$

where $I$ is the acoustic intensity and $\theta$ is the correction angle an agent adds to its previous weighted heading in case it is not going in the direction of increasing acoustic intensity. The corresponding weighted direction of an agent, $i$, based on (7) and (8) is computed every $\tau$ seconds as

$$\mathbf{d}_{\mathrm{w}_i}(t) = b_{\mathrm{s}} \cdot \mathbf{d}_{\mathrm{s}_i}(t) + (1-b_{\mathrm{s}})\mathbf{d}_{\mathrm{a}_i}(t) \quad (9)$$

where $b_{\mathrm{s}} \in [0.5, 1]$ is the source biasing coefficient where any values of $b_{\mathrm{s}} < 0.5$ fail in the source localization for any of the collective behaviour models. Note that higher values of $b_{\mathrm{s}}$ mean less team cohesion and vice versa. Now, we can write the desired direction of an agent, $i$, at time, $t$, as

$$\mathbf{d}_{\mathrm{d}_i}(t) = \begin{cases} \mathbf{d}_{\mathrm{r}_i}(t) & \text{if } n_{\mathrm{r}}(t) \neq 0 \text{ and } r_{\mathrm{r}} \neq 0 \\ \mathbf{d}_{\mathrm{w}_i}(t) & \text{otherwise} \end{cases} \quad (10)$$

Table 1: Symbols, their description and values explored during simulation.

| Sym. | Description | Value(s) |
|---|---|---|
| $N$ | Total number of team members | $\{1, 3, 5, 10, 15, 20\}$ |
| $r_s$ | Radius of the success zone | 50 m |
| $r_a$ | Neighbourhood radius / Radius of the attraction zone | {150,300,600} (m) |
| $r_r$ | Radius of the repulsion zone | $\{0, 7.6\}$ (m) |
| $r_{min}$ | Minimum radius of the repulsion zone | 3.8 m |
| $l$ | Length of an agent | 0.8 m |
| $s$ | Speed of an agent | $1.5\,\mathrm{m\,s^{-1}}$ |
| $\dot{\theta}_{max}$ | Maximum turning rate of an agent | $35\,^\circ\,\mathrm{s}^{-1}$ |
| $\tau_r$ | Sampling time of the short-range repulsion models | 1 s |
| $\tau$ | Sampling time of the long-range attraction models and the source bias model | $[1, 1000]$ (s) |
| $b_s$ | Source biasing coefficient | $[0.5, 1.0]$ |
| $\theta$ | Correction angle | $[0, 180°]$ |

Also, note that (10) accounts for all the collective behaviour models, i.e., the short-range repulsion and the long-range attraction behaviours of UV, C and PS models.

A Genetic Algorithm [44] is used to optimize the parameters, $b_s$, $\theta$ and $\tau$. The fitness function is the mean arrival time of 1024 simulation runs. Inspired by [1], the number of simulation runs is calculated from the Vargha-Delaney's A-measurement test [68] which ensures similar inter-simulation fitness distributions. We investigate the performance impact of varying the radius of the attraction zone (neighbourhood radius), $r_a$ and SNR for different team size, $N$. A table for all the values of the parameters explored is given in Table 1. The agent length, speed and the maximum turning radius are taken from field experiments on a miniature submarine as shown in Fig. 3. We assume a constant speed operation in the simulations with speed, $s$, of each agent set to $1.5\,\mathrm{m\,s^{-1}}$.

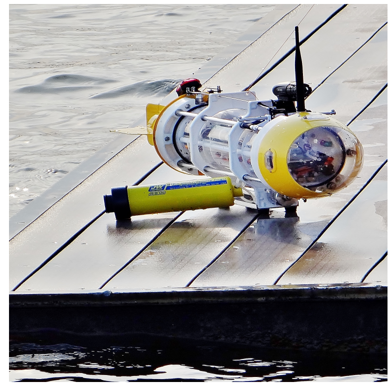


Figure 3: A miniature submarine called Swarmbot during field experiments at Pandan Reservoir, Singapore.

# 5. RESULTS & DISCUSSION

The focus is to compare the PS model with limited neighbour information against the UV and C models with complete neighbour information under different operating conditions.

## 5.1 Without the Short-range Repulsion

First we investigate the effect of having only the long-range attraction in the UV, C and PS models, i.e., we set $r_r = 0$ for different team sizes as shown in Fig. 4. Figure 4(a) shows the mean arrival times of different team sizes. Each mean arrival time is representative of $49 \times 10^3$ simulation runs. It is interesting to note that for smaller teams, PS registers better performance in Fig. 4(a), using significantly more cohesion (lower $b_s$) than the other models in Fig. 4(b). However as the team size increases, the difference narrows down with all the three models displaying similar performance at $N = 15$. For all the simulated values of $N$, there is neither any significant difference between the performance of the UV and C models nor in their optimal control parameter values as can be seen in Fig. 4(b), Fig. 4(c) and Fig. 4(d). As for the correction angle, $\theta$, all the three models use nearly the same values till $N = 5$ but for $N = 10$ and beyond, PS in Fig. 4(c) switches abruptly to a new correction angle strategy. This also corresponds in Fig. 4(b) to the cohesion levels switching abruptly to a higher value.

## 5.2 The Advantage Threshold

The dotted magenta line in Fig. 4(a) and Fig. 5(a) signifies the *advantage threshold* where the collective behaviours are inactive. The advantage threshold is important in the biological systems where researchers are interested in knowing if an individual enjoys any advantage living in a group rather than being alone and if there is an optimal group size [61, 57]. When the arrival times in a team ($N > 1$) remain below the advantage threshold, it signifies an individual benefitting from a group. It can be seen that all the collective behaviour models show significant improvement for small teams except at $N = 3$ in the case of the C and UV models.

## 5.3 With the Short-range Repulsion

We set $r_r = 2r_{min}$ in the UV, C and PS models to investigate the effect of the short-range repulsion on source localization arrival times. Figure 5(a) shows the arrival times for the neighbourhood radii of 300 m and 600 m. It is interesting to note the slight degradation in mean arrival times if we compare Fig. 4(a) and Fig. 5(a). The only exception is at $N = 3$ where the C and UV models have shown significant improvement. To show nearly the same performance as in the case of Fig. 4(a), the attraction radius needs to be twice as much when the short-range repulsion is also active. Also note that the PS model loses its slight advantage over the C and UV models once the neighbourhood radius is increased to 600 m. Fig. 5(b) emphasizes this fact where for the case of an increased neighbourhood radius, the C and UV models have utilized more cohesion than the PS model.

Also, in Fig. 5(a), increasing the team size up to a certain limit adds more benefit for an individual, however beyond that limit, the arrival times start degrading. In other words there seems to be an optimal team size for an individual in this case. The PS model suffers the most from this phenomenon where for $r_a = 600$ m, it is performing nearly at par with the C and UV models with $r_a = 300$ m at $N = 20$. The degradation in performance may have a link with the

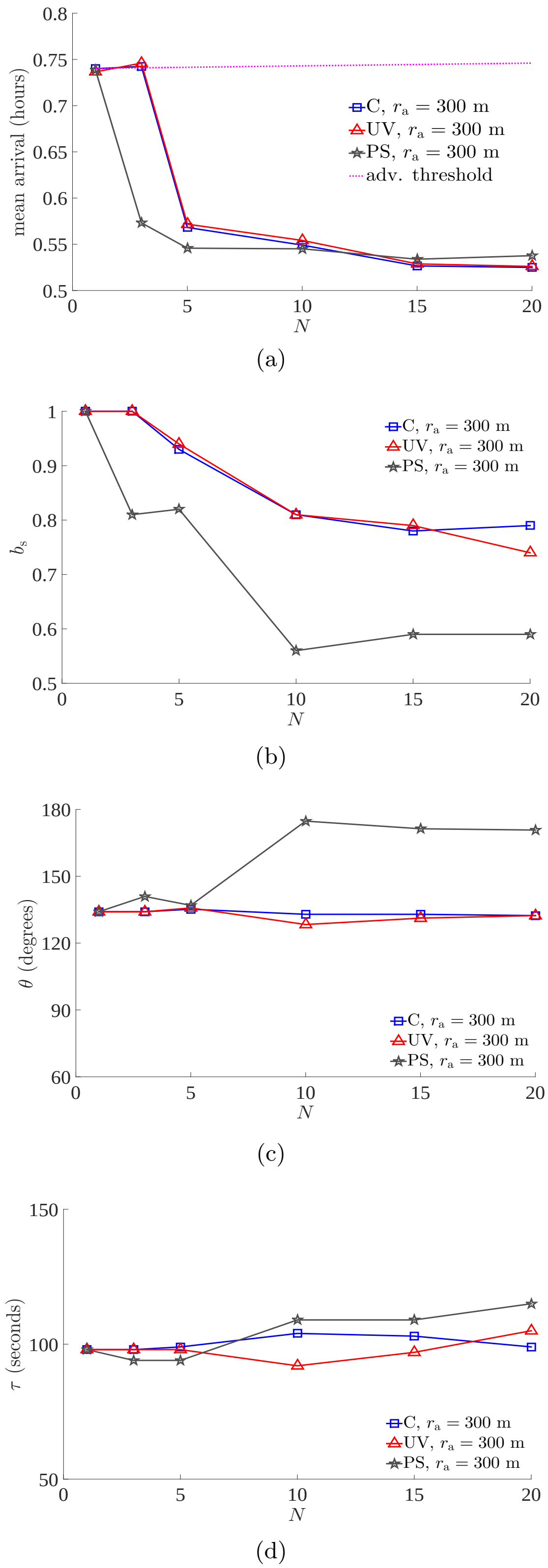



Figure 4: Comparative performance and optimal parameters of the Centroid (C) model, Unit Vector (UV) model and Passive Sensing (PS) model as a function of number of agents without short-range repulsion: (a) Mean arrival time (b) Source biasing coefficient. (c) Correction angle. (d) Sampling time.

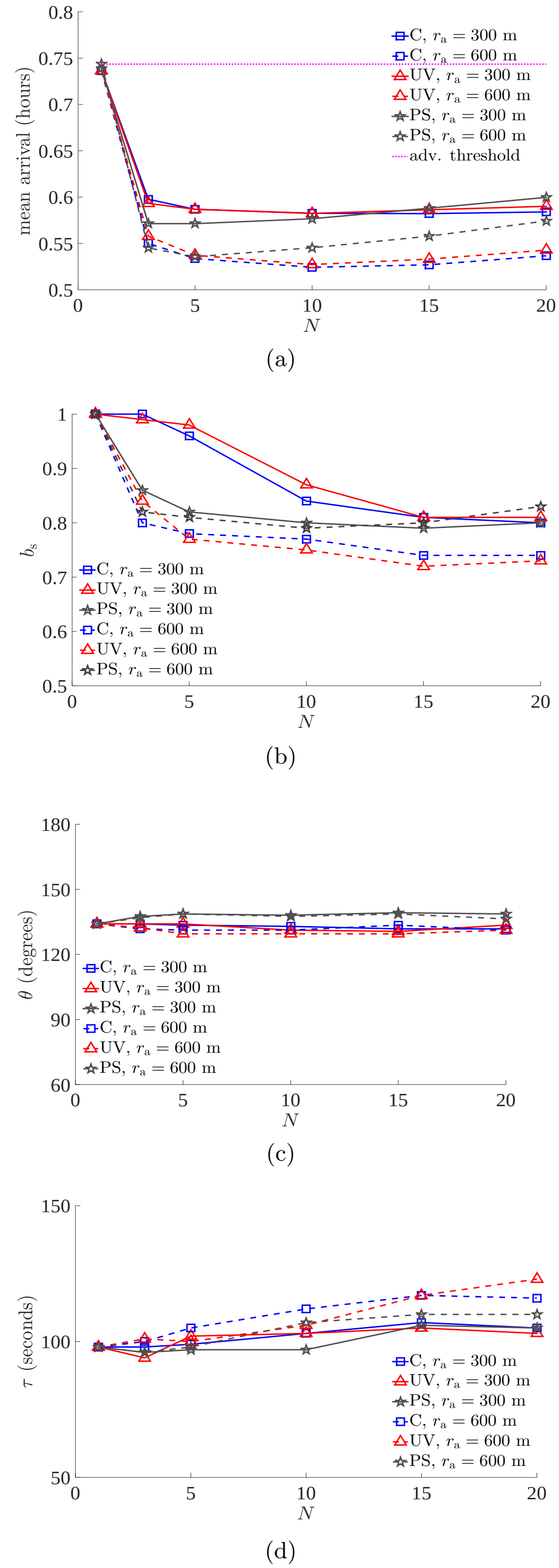
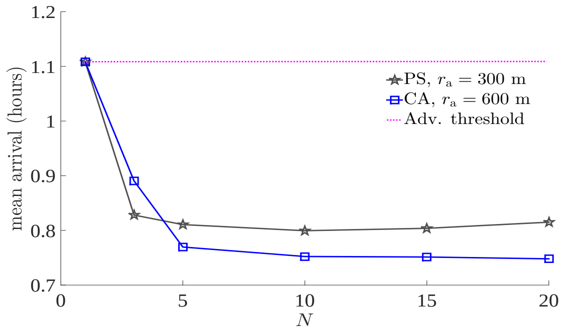
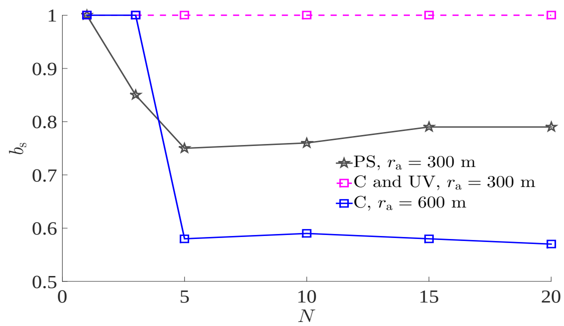



Figure 5: Comparative performance and optimal parameters of the Centroid (C) model, Unit Vector (UV) model and Passive Sensing (PS) model as a function of number of agents withshort-range repulsion: (a) Mean arrival time (b) Source biasing coefficient. (c) Correction angle. (d) Sampling time.




(a)




(b)

Figure 6: Performance of the Passive Sensing (PS) model in a reduced SNR scenario: a) Comparative performance against the advantage threshold and Centroid (C) model with double the neighbourhood radius. (b) Comparison of cohesion levels for PS, Centroid (C) and Unit Vector (UV) models.

increasing cohesion levels and number of agents. We can see the general trend in Fig. 5(b) where teams increase their cohesion levels as their size increases. However, this also increases the average number of times an individual has to avoid collisions during a mission. Since PS suffers from the incomplete neighbourhood information and consequentially responds only to the nearest neighbour, the behaviour may make the team confused with growing cohesion and team size [35]. The effect may be seen in Fig. 5(b) where PS starts retreating back to lower cohesion levels to perform optimally with larger team sizes.

The correction angle remains effectively constant for each of the collective behaviours in Fig. 5(c) throughout the range of the team size and also for both the neighbourhood radii.

Sampling times in Fig. 5(d) behave similarly for all the collective behaviours for the neighbourhood radius of 300 m. However, for the case of neighbourhood radius set to 600 m, UV displays a pattern of a slow increase in the sampling time as a function of team size. In general, a large sampling time in the range of 100 s to 110 s ensures enough agent traversal in the search space to collect an uncorrelated sample and contribute towards an implicit averaging process that would be beneficial as a whole.

## 5.4 Lower Intensity Cues

We assume a degraded SNR by increasing the ambient noise levels to 118 dB re 1 $\mu$Pa. The comparative performance of the PS model for the degraded SNR is shown in Fig. 6(a) against the advantage threshold. It is interesting to note that for a neighbourhood radius of 300 m, both the C and UV models lose the ability of providing an agent with the benefit of team cohesion as shown in Fig. 6(b) where both operate with $b_s = 1$. However if we increase the neighbourhood radius to 600 m we can see that C model performs significantly better in Fig. 6(a) using higher cohesion levels as shown in Fig. 6(b).

The PS model keeps its trends in Fig. 6(a) and Fig. 6(b) as were described in Section 5.1 for Fig. 5(a) and Fig. 5(b). There seems to be an optimal group size between $N = 5$ and $N = 10$ in Fig. 6(a) where onwards, the PS model starts reducing its cohesion levels in Fig. 6(b).

## 5.5 Agent Trajectories

Agent trajectories from a simulated source localization mission for a team of 10 agents without the short-range repulsion behaviour are shown for the C, UV and PS models in Fig. 7(a), Fig. 7(b), Fig. 7(c) respectively. The red dots show the trajectory for a specific agent in a team, arrival of which marked the mission as a success. Since, the PS model boosts significantly higher cohesion levels in Fig. 4(b) for $N = 10$ as compared to the C and UV models, the agent trajectories for the PS model in Fig. 7(c) compliment that finding when compared to the trajectories of the C and UV models. As a whole, the team seems more cohesive and focussed towards the source for the PS model. For the short-range repulsion active, the three trajectories for C, UV and PS models are given in Fig. 7(d), Fig. 7(e), Fig. 7(f) respectively which are similar for nearly the same cohesion levels in Fig. 5(b). In summary, the trajectory response of the PS model is not significantly different than C and UV models and conserves the same pattern despite the loss of information.

# 6. CONCLUSION

We presented a bio-inspired model which invokes collective behaviour in a multi-agent system using passive sensing without any explicit inter-agent communication. The passive sensing model assumes two sensors per agent, one on its right side and one on its left side. Both the sensors help an agent detect the majority of its neighbours either in its left or right half space. For a source localization problem, we analyzed the comparative performance of the passive sensing model with the well-known school-of-fish collective behaviour models (C and UV) aided by ideal explicit communication. It was shown that the proposed approach performs better than or at par with C and UV models for teams with small number of agents (3 – 20) in certain conditions. Especially, in conditions involving constrained neighbourhood radii and higher background noise levels, C and UV models failed to extend any benefit to an individual agent whereas the passive sensing model extended significant benefit. Moreover, the proposed strategy was shown to make up for the information loss by boosting higher cohesion levels in a team than the other models. However, it was also shown that for larger teams, the passive sensing approach reduces the cohesion levels to avoid agent confusion due to the short-range repulsion behaviour.

In general, the proposed approach shares similar trends with the other collective behaviour approaches, e.g., in the effect of the long-range attraction and the short-range repulsion on performance, optimal parameter values and agent

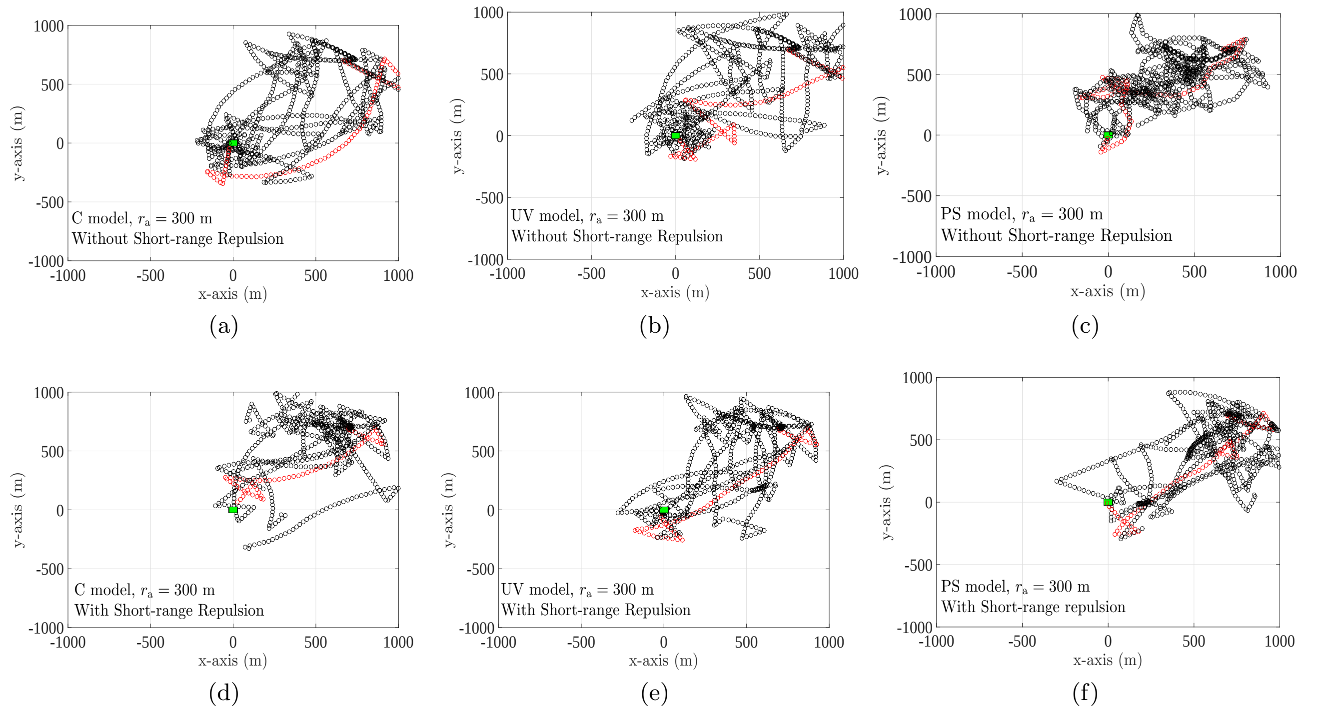



Figure 7: Trajectories of the collective behaviours without short-range repulsion: (a) C model. (b) UV model. (c) PS model. Trajectories with short-range repulsion: (d) C model. (e) UV model. (f) PS model.

trajectories. There is a need to investigate the short-range repulsion behaviour more in terms of the source localization problems. For all the collective behaviour models, the short-range repulsion shows some performance degradation. It may have to do with an agent facing competition near the source due to the earlier arrivals of other agents. Given the indispensable nature of collision avoidance control in many practical multi-agent systems, the short-range repulsion needs to be optimized such that it can accommodate larger team sizes.

We can also make some general conclusions from the results shown in this paper. It was shown that a small team requires a large enough neighbourhood radius to have sufficient uncorrelated cue samples. Collective implicit averaging works well with the uncorrelated cue samples but has a detrimental effect on the collective decision making of a team otherwise [37]. The cue sampling times also showed to have a complimentary effect. The sampling times were optimized by an evolutionary algorithm and the optimal values suggest that an agent needs to traverse more in space to gather uncorrelated samples of a cue. This warrants a more profound investigation of the relationship between the parameters like the neighbourhood radius, sampling time, team size and the spatial correlation of a cue.

## 7. ACKNOWLEDGMENTS

The authors would like to thank Prasad Anjangi from the Acoustics Research Lab for providing helpful suggestions in improving the layout of the manuscript. Also, the authors are thankful to the four anonymous reviewers for their detailed reviews, full of helpful critiques and insights which resulted in an improved manuscript and helped us in broadening our vision for the future research.

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