Adaptive Sampling and Collective Behaviour in a Small Team of AUVs for a Source Localization Problem

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Abstract—**In this paper we present an adaptive sampling approach for a distributed multi-AUV source localization algorithm. The algorithm is composed of different bio-inspired behaviours for invoking collective behaviour in a multi-agent system. The adaptive sampling approach shows significant performance improvement in terms of mean arrival times over the previously reported static sampling approach for both the presented arrival scenarios. The adaptive sampling approach also boosts the maximum levels of team cohesion, suggesting its ability to maximize the benefit from the social information. Apart from better mean arrival times, the adaptive sampling approach also results in significantly reduced variance of the arrival-time distribution.**

I. Introduction

In the last decade or so, multi-agent systems have significantly impacted various fields of applied engineering research [1]–[2]. Applications involving autonomous vehicles such as Unmanned Ground Vehicles (UGVs), Unmanned Aerial Vehicles (UAVs) and Autonomous Underwater Vehicles (AUVs) have significantly benefitted from these multi-agent strategies [3]–[4]. A significant share of the multi-agent research [5]–[6] has been inspired from natural animal swarms [7]–[8]. Among other engineering problems, source localization is a strong candidate problem for multi-agent systems and hence different bio-inspired solutions have been proposed [9]–[11].

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 [12]. Due to the possibility of a strong spatial correlation in the source's intensity samples, the multi-agent system as a whole needs to span a sufficiently large space to be able to collect enough uncorrelated samples to aid the collective decision making [13]. Given a small team of AUVs, the phenomenon of uncorrelated sampling will require much larger neighbourhoods than seen in the natural swarms, such as the school-of-fish. Larger neighbourhoods require long-range communication underwater which is practically achievable only by using acoustic communication which has various implementation challenges [14]. Performance of explicit communication based strategies [15]–[16] suffer substantially due to communication constraints.

Furthermore, in biological models of the animal collective behaviour, the information transfer generally means exchange of neighbours' position information within a confined neighbourhood. Reliable acquisition of position estimate underwater is a challenging and an expensive problem to solve. In such harsh environments, having an implicit communication based strategy that is only based on the passive sensing of the environment, allows the multi-agent system to operate cooperatively potentially without a complete breakdown. However, at present, there are no known implicit communication based strategies that can benefit a source localization task by invoking collective behaviour in a multi-agent setup. There has been some work in that direction as given in [11] but the given sensor model does not address the problem of acquiring neighbours' position estimates.

In this paper we build on a significantly modified sensor model [17] which addresses the practical issues of bio-inspired models such as [11]. The modified sensor model only requires an AUV to carry out passive sensing of the environment to acquire information about its neighbours. The required information is neither in terms of the position estimates nor the number of neighbours. An AUV, equipped with only two hydrophones, requires to distinguish where the majority of its neighbours lie, either in its left half space or the right half space. Given the practical sensor model, the focus of this paper is on investigating the effect of an adaptive sampling strategy on the localization performance in a multi-AUV setup. We define the source localization problem in Section II. We list the individual behaviours of an AUV along with the overall resultant behaviour or the control algorithm in Section III. We present the novel adaptive sampling strategy in Section IV. The details pertaining to the optimization of the control parameters and the simulation setup are given in Section V. A detailed discussion pertaining to the results for two different localization scenarios is presented in Section VI. We finally conclude in Section VII.

II. Problem Statement

Let us define the source localization problem considered in this paper. We assume an acoustic point-source located at the origin of a two-dimensional search plane. Arrival time is defined as the time taken by a specific AUV to enter a circular success zone around the source and not diverge from it following the initial entry. We focus on two arrival scenarios in this paper, i.e., the first arrival and the last arrival. In the first arrival scenario, the first AUV to enter the success zone successfully completes the mission. For the last arrival, we require all the AUVs to enter the success zone to successfully complete the mission.

III. Behavioural Models

We adopt three behavioural models in this paper. Each behaviour is described briefly in this section with appropriate references for a more detailed discussion.

A. Target Drive

The Target Drive (TD) control module helps an individual localize a source without being dependent on any social information. First introduced in [11], TD consists of a simple behaviour where an individual continues to move straight if it senses increasing sound levels or takes a counter-clockwise correction turn, θ_c, otherwise. In this paper, we optimize θ_c using a Genetic Algorithm (GA) [18]. Therefore, depending on the given localization scenario, the optimized correction angle may be different than the static $90°$ correction angle as reported in [11].

B. Group Cohesion

The Group Cohesion (GC) control module is inspired from the long-range attraction behaviour in a school of fish [19] where an AUV biases itself towards its neighbours. However, the long-range attraction based models generally require communication of neighbours' position information which is especially a hard and an expensive problem to solve underwater. The GC model considered in this paper is based on a passive sensing scheme as given in [17] and uses only two sensors per AUV. Using the two sensors on its two sides, an AUV detects the majority of its neighbours either in its left or the right half plane and takes a $90°$ turn in the direction of the neighbour majority. The attraction neighbourhood radius, r_{GC}, is effectively the maximum range of neighbour detection.

C. Collision Avoidance

Similar to GC, the Collision Avoidance (CA) control module is inspired from the short-range repulsion phenomenon observed in a school of fish. An AUV tags its neighbour as a threat if it enters into its private space, i.e., inside a repulsion neighbourhood radius, r_{CA}. Using the two sensors, an AUV can estimate the relative distance to the nearest threat and the half in which it resides. Then the AUV initiates a turn in the opposite half with a turning rate that is a function of the estimated distance to the nearest threat. For a detailed behaviour formulation and associated practical issues, see [17].

D. Resultant Behaviour

Let us now summarize the resultant behaviour of an AUV which is a consequence of the three underlying individual behaviours. CA operates with the highest priority and in case an AUV detects a threat in its private space, all the other behaviours are suspended and the AUV follows the CA-dictated direction vector, $\mathbf{\Theta}_{\text{CA}_n}$. CA also operates on a much shorter time scale, i.e., with a sampling time of T_{CA} seconds.

The TD and GC behaviours are coupled by a weighted average approach and operate at the same time scale with a sampling time of T seconds. The weighted direction vector for the n^{th} AUV is given as

$$\mathbf{\Theta}_{\text{W}_n} = \eta \mathbf{\Theta}_{\text{TD}_n} + (1-\eta)\mathbf{\Theta}_{\text{GC}_n} \tag{1}$$

where $\mathbf{\Theta}_{\text{TD}_n}$, $\mathbf{\Theta}_{\text{GC}_n}$ are the unit directional vectors dictated by the TD and the GC modules respectively and $\eta \in [0.5, 1]$ is the drive coefficient. Source localization requires $\eta > 0.5$, i.e., more than $50\,\%$ weight on the source-related (non-social) information. Finally, we can write the resultant direction vector of the AUV as

$$\mathbf{\Theta}_{\text{R}_n}(t) = \begin{cases} \mathbf{\Theta}_{\text{CA}_n}(t) & \text{if AUV detects a threat} \\ \mathbf{\Theta}_{\text{W}_n}(t) & \text{otherwise} \end{cases} \tag{2}$$

IV. Adaptive Sampling

Adaptive Sampling (AS) updates the synchronous Static Sampling (SS) approach given in [11] for TD and GC modules. We replace the constant sampling time T with a dynamic sampling time, $T_{i_n} \triangleq t_{i+1} - t_i$ for an n^{th} AUV, where i^{th} sample is taken at time, t_i, and $(i+1)^{\text{th}}$ sample is taken at time, $t_i + T_{i_n}$. We set the value of the asynchronous sampling time as a function of received root mean square (rms) pressure, $P_n(t)$, as

$$T_{i_n} = \frac{T}{1 + e^{c(P_{n_{\text{dB}}}(t_i) - b)}} + T_{\min} \tag{3}$$

where $T_{\min}$ is the minimum sampling time, $T_{i_{n_{\max}}} = T + T_{\min}$ is the maximum sampling time, $c, b \in \mathbb{R}^+$ are constants which respectively determine the rate-of-transition from $T_{i_{n_{\max}}}$ to $T_{\min}$ and the mean value of $P_{n_{\text{dB}}}(t)$ around which the transition starts and ends. An example of T_{i_n} being a function of $P_n(t)$ is given in Fig. 1 where $T = 200$ s, $b = 120$ dB, $c = 0.2$ and $T_{\min} = 5$ s.

The idea behind using an adaptive sampling time as a function of received pressure emanates from the underlying relationship between the initialization distance and the radius of the success zone. The initialization distance, r_0, is defined

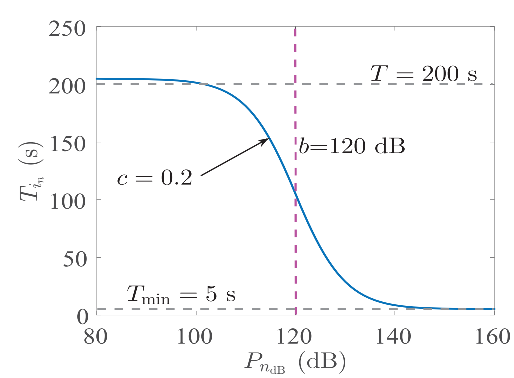

Fig. 1: An example of the adaptive sampling approach with $T = 200$ s, $b = 120$ dB, $c = 0.2$ and $T_{\min} = 5$ s.

TABLE I: Symbols, their description and values explored during simulation.

Sym.	Description	Value(s)
N	Total number of team members	10
r_0	Initialization distance	{1000,3000} (m)
a	Dimension of each side of the initialization square region	20 m
r_s	Radius of the success zone	{10,50} (m)
r_GC	Attraction neighbourhood radius	{600,1800} (m)
r_CA	Repulsion neighbourhood radius	7.6 m
l	Length of an AUV	0.8 m
s	Speed of an AUV	$1.5\,\mathrm{m\,s^{-1}}$
$\dot{\theta}_\text{max}$	Maximum turning rate of an AUV	$35\,^\circ\,\mathrm{s}^{-1}$
T_CA	Sampling time of CA	1 s
T	Sampling time of TD and GC	$[1, 1000]$ (s)
T_min	Minimum sampling time	1 s
η	Drive coefficient	$[0.5, 1.0]$
θ_c	Correction angle	$[0, 180°]$
b	Transitional value of $P_{n_\text{dB}}(t)$	$[0, 180]$ (dB)
c	Transition rate of adaptive sampling	$[0, 0.5]$

as the mean starting distance of N AUVs from the source location where each agent is initialized with a random pose within a square region of dimensions $a \times a$ m^2. The radius of the success zone, r_s, is generally very small as compared to r_0. Starting thousands of meters away from the source, an AUV thrives on larger T to clearly distinguish between increasing or decreasing sound levels. However as large a T would be, it will be as difficult to enter inside a success zone with a small radius (tens of meters). Hence an ideal scenario would be to have a larger sampling time when an AUV is further away from the acoustic source and a shorter sampling time when it is closer. The only cue available to the AUV is the sensed rms pressure at some spatial point and if the AUV can *hear* for the acoustic source at a higher rate as it senses a higher-magnitude rms pressure, the strategy should result in a significantly better arrival time.

V. Parameter Otpimization & Simulation Setup

We optimize θ_c in TD, η in (1), the sampling time T and the associated adaptive sampling parameters, b and c in (3) by using a GA. The fitness function of each individual in the GA is the mean arrival time over 1024 simulation runs. The number of simulation runs have been calculated using the Vargha Delaney's A-measurement test [20] to ensure similar distributions for the entire population. The mean arrival times associated with each of the arrival scenarios (as discussed in Section II) are referred to as the First Arrival Time (FAT) and the Last Arrival Time (LAT). Once the best solution (optimal set of parameters) is acquired from the GA for a given scenario and operating conditions, we run $49\,152$ simulated missions for the particular solution set to report the statistical data (as shown in Fig 2, Fig 3 and Table II).

We initialize a team of $N = 10$ AUVs, each with a random pose within a square region having an area of 20×20 m^2 and its center located r_0 m away from the acoustic source. The initialization distance, r_0 is either set to $1000\,\mathrm{m}$ or $3000\,\mathrm{m}$ to analyze performance under different operational ranges and cue intensities. The radius of the success zone, r_s is set to $10\,\mathrm{m}$ for FAT and $50\,\mathrm{m}$ for LAT. For sensing the intensity of the source, we use a sound propagation model with spherical spreading suitable for deep underwater environments [21]. For the source, we assume a sound pressure level of $180\,\mathrm{dB}$ re 1 μPa at $1\,\mathrm{m}$ away in the bandwidth of interest. The source level corresponds to the sound levels of many commercially available underwater locator beacons. For the ambient noise, we assume noise level of $118\,\mathrm{dB}$ re 1 μPa in the bandwidth of interest which corresponds to the shallow water noise in a real-world scenario [22]. The agent length, l, speed, s, and the maximum turning radius, $\dot{\theta}_\text{max}$, are taken from field experiments on a miniature submarine called Swarmbot [17]. We assume a constant speed operation in the simulations. The CA-related parameters have been tuned in a way to give $100\,\%$ success in avoiding collisions in all the $49\,152$ simulated missions. For an easy reference, all the parameters' symbols, descriptions and explored values are given in Table I.

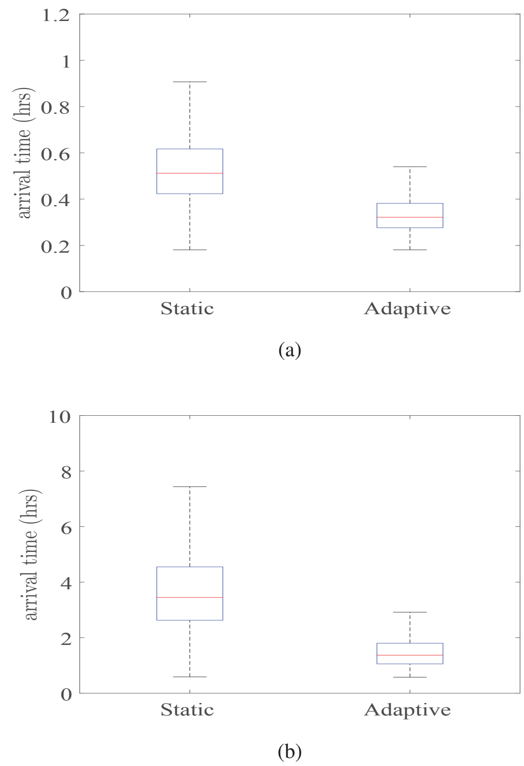

Fig. 2: FAT based comparative performance of using a static sampling approach and an adaptive sampling approach: (a) For an $r_0 = 1000$ m. (b) For an $r_0 = 3000$ m.

VI. Results & Discussion

A. *Scenario#1: First Arrival Results*

For an initialization distance, r_0, of $1000\,\mathrm{m}$, FAT performance improves by $35.85\,\%$ using the adaptive sampling strategy as compared to the static sampling strategy, as shown in Fig. 2(a). The comparative performance difference is even more significant, i.e., $59.33\,\%$ as the initialization distance is increased to $3000\,\mathrm{m}$ as shown in Fig. 2(b).

For both the sampling strategies, optimal parameter values for Fig. 2(a) and Fig. 2(b) are given in Table II. The drive

Arrival scenario	r_{GC} (m)	r_0 (m)	Sampling approach	η	θ_{c} (deg)	b (dB)	c	T (s)	Mean arrival time (hrs)
FAT	600	1000	Static	1.000	136.70	–	–	87.00	0.530
			Adaptive	1.000	72.53	129.80	0.189	149.00	0.340
		3000	Static	0.960	142.40	–	–	261.00	3.590
			Adaptive	0.980	77.30	121.60	0.246	676.00	1.460
LAT	600	1000	Static	0.575	176.17	–	–	100.00	0.865
			Adaptive	0.527	169.00	135.66	0.194	137.00	0.776
		3000	Static	0.546	176.20	–	–	130.00	14.04
			Adaptive	0.506	178.65	136.15	0.187	170.00	13.35
LAT	1800	1000	Static	0.591	180.00	–	–	105.00	0.855
			Adaptive	0.557	179.33	132.65	0.180	167.00	0.743
		3000	Static	0.692	178.70	–	–	192.00	10.172
			Adaptive	0.506	178.70	129.00	0.219	431.00	7.049

TABLE II: Optimization values and mean arrival times for Static and Adaptive sampling approaches and different initialization distances.

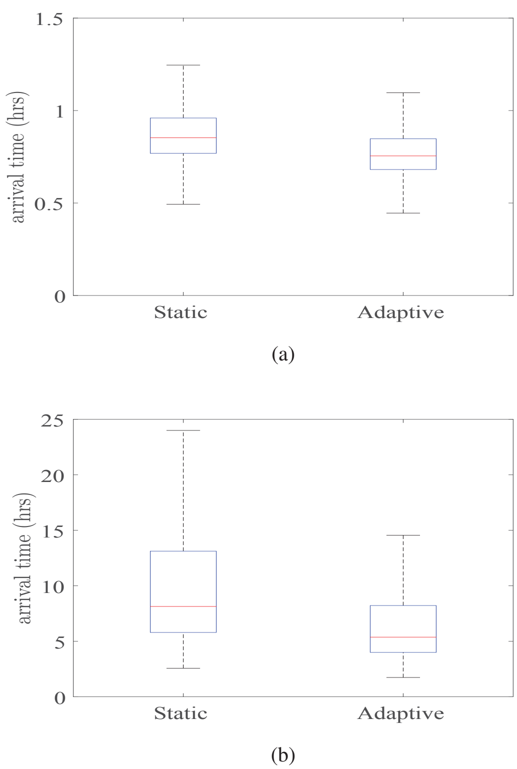

Fig. 3: LAT based comparative performance of using a static sampling approach and an adaptive sampling approach: (a) For an $r_0 = 1000$ m. (b) For an $r_0 = 3000$ m.

coefficient, η, being close to 1.00 agrees with the earlier investigations related to FAT where an AUV does not rely on the social information [11].

The correction angle, θ_{c}, for static sampling approach is in the range of 135° to 145° and agrees with the results for small teams, i.e., $N < 10$ in [17] where mean Specific Arrival Time (SAT) was the performance metric. However, it is with the adaptive sampling approach that we see a significantly smaller correction angle in the range of 70° to 80°.

The optimal sampling time, T for the static sampling approach scales linearly with r_0. However, for the case of the adaptive sampling, the increase is much more exaggerated. The larger T makes sense since it helps the AUV to traverse more when far away from the source and traverse much less as it gets close to the success zone. The transition rate, c, and the mean transitional value, b, seem to compliment each other. For $r_0 = 1000$ m, T is $149\,\mathrm{s}$ whereas for $r_0 = 3000$ m, it is $676\,\mathrm{s}$. Hence the adaptive sampling curve (example shown in Fig. 1) falls earlier and more sharply for the larger T.

B. *Scenario#2: Last Arrival Results*

For an initialization distance of $1000\,\mathrm{m}$ and attraction neighbourhood radius of $600\,\mathrm{m}$, there was a comparative improvement of $10.28\,\%$ in LAT performance for using the adaptive sampling approach over the static sampling approach as shown in Fig. 3(a) and Table II. Under the same conditions but for $r_0 = 3000$ m, LAT performance in general, degrades substantially and the comparative performance improvement was only $4.91\,\%$ as shown in Table II. However for $r_0 = 3000$ m, if we increase r_{GC} to $1800\,\mathrm{m}$, we see significant improvement in LAT performance in general as shown in Fig. 3(b). Also, we see a more significant improvement of $30.77\,\%$ in mean arrival times (see Table II) using the adaptive sampling approach over the static sampling approach.

For both the sampling strategies, optimal parameter values for $r_0 = \{1000, 3000\}$ (m) and $r_{\mathrm{GC}} = \{600, 1800\}$ (m) are given in Table II. The drive coefficient, η, shows high levels of group cohesion or schooling for LAT which is in agreement to the earlier findings in [11]. In general, adaptive sampling approach thrives on higher group cohesion levels than the static sampling approach. This may be because of the adaptive sampling maximizing the benefit from the underlying phenomenon of implicit averaging. For example, for $r_0 = 3000$ m and $r_{\mathrm{GC}} = \{600, 1800\}$ m, drive coefficient is nearly 0.50 which is the maximum possible group cohesion.

For LAT, the optimal θ_{c} in general remained in the range of 170° to 180° for both the static and the adaptive sampling approaches and agrees with the results for team sizes $N \geq 10$ in [17] where analysis was done for SAT with static sampling.

From the results in Table II and the discussion so far, it seems that $r_{\mathrm{GC}} = 600$ m, is simply not a sufficient neighbourhood radius for $r_0 = 3000$ m. On the other hand for $r_0 = 1000$ m, $r_{\mathrm{GC}} = 1800$ m does not seem to add any significant improvement over $r_{\mathrm{GC}} = 600$ m. This phenomenon suggests that there is a minimum attraction neighbourhood radius beyond which there is no significant improvement in the arrival times.

Analyzing the behaviour of the optimal T as a function of the ratio of r_{GC} to r_0 yields some interesting findings. From the preceding discussion, we know that the static sampling approach is limited in terms of how large its T can be. The optimal T is a trade-off between the benefit of traversing more in the earlier stages of the localization process and traversing less in the later stages. This can be seen for the case of $r_0 = 1000$ m and r_{GC} set to either $600\,\text{m}$ or $1800\,\text{m}$ where T has not changed significantly, i.e., a change of only $5\,\%$. This suggests that the attraction neighbourhood radius of $600\,\text{m}$ is not a limiting factor in this case (ratio of r_{GC} to r_0 being 0.6) with T already approaching its optimal value for the static sampling case. However, when we look at the case of $r_0 = 3000$ m, we find that T has increased about $48\,\%$ for the larger neighbourhood radius of 1800 m. This suggests that $r_{\text{GC}} = 600$ m (ratio of r_{GC} to r_0 being 0.2) is the performance limiting factor in this case where T was not limited by the sampling strategy rather how far an AUV can travel before it can no longer benefits from sufficient social information. It may be that some minimum number of neighbouring AUVs need to be present inside the attraction neighbourhood of an AUV to provide it with enough good samples to exploit the phenomenon of implicit averaging.

Now, let us consider the optimal parameter values and the arrival performance of the adaptive sampling approach in Table II. The adaptive sampling strategy helps overcome the limitation on T as was seen for the case of static sampling approach. For example, for $r_0 = 1000$ m, T has increased $22\,\%$ for the case of $r_{\text{GC}} = 1800$ m as compared to $r_{\text{GC}} = 600$ m, resulting in a performance improvement of $4.25\,\%$. This phenomenon is even more exaggerated where for $r_0 = 3000$ m, T has increased $154\,\%$ for the case of $r_{\text{GC}} = 1800$ m as compared to $r_{\text{GC}} = 600$ m, resulting in a performance improvement of $30.77\,\%$.

Considering the given simulation setup, we can say that the arrival performance depends on the sampling strategy or the ratio of r_{GC} to r_0 . In a more general setting, it will also depend on the team size as increasing the team size in certain scenarios may reduce the minimum ratio of r_{GC} to r_0 required for the best arrival times [17].

The transition rate, c, and the mean transitional value, b, behave the same way as was the case for FAT and hence the same behavioural explanation applies.

C. Uncertainty of Arrival

It is important to note that in both the arrival scenarios, i.e., FAT and LAT, the relative uncertainty of the arrival or variance of the arrival times has been reduced significantly while using the adaptive sampling approach as shown in Fig. 2 and Fig. 3. This trend holds in general for different operating conditions.

VII. Conclusion

We presented an adaptive sampling approach for a distributed multi-AUV source localization algorithm. The algorithm is composed of three bio-inspired behaviours, each of which conforms to the practical constraints underwater. Two arrival scenarios, i.e., the first arrival and the last arrival, were presented for defining the respective performance metrics, i.e., FAT and LAT. In a given arrival scenario, the optimal solutions for both the static and the adaptive sampling approaches were acquired using a GA. The results show that the presented adaptive sampling approach results in significant performance improvement over the static sampling approach for both FAT and LAT.

For LAT, results show that the adaptive sampling approach also boosts the maximum levels of team cohesion which suggests its ability to maximize the benefit more from the social information. This finding mandates a more rigorous study to explore the effects of having an adaptive sampling strategy in the biological schooling models for source localization problems. Apart from better arrival times, the adaptive sampling approach also results in significantly reduced uncertainty in arrival times.

Given the two sampling strategies, we also investigated the effect of the ratio of the attraction neighbourhood radius to the initialization distance on the arrival performance. We substantiated that the adaptive sampling eliminates the limitations of the static sampling strategy, however, the ratio of the attraction neighbourhood radius to the initialization distance is still an important consideration. This limitation is also dependent on the team size which we kept constant at 10 AUVs in this paper. However, it will be interesting to analyze the relationship between team size and the required minimum ratio to maximize the localization performance.

The adaptive sampling strategy is a leap towards investigating more dynamic behaviours. This is especially true for the bio-inspired source localization models since it is highly unlikely that an individual would not alter its behaviour based on changing social or ambient information. In future, we wish to explore more such behaviours that would help us maximize the benefit from the collective behaviour of a multi-agent system. This may also give us an opportunity of better understanding the animal collective behaviour in nature such as long-distance migrations of massive fish schools.

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