On Social Behaviours and Sampling Times in Multi-Agent Source Localization

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Abstract: We investigate the optimal sampling times of school-of-fish social behaviours for a multi-agent source localization problem. We explicitly include the neighbour alignment social behaviour and investigate its relative role in terms of the arrival-time performance. For two different individualistic behaviours, results show that the social behaviours work significantly better when their operation is coupled together at the same time-scale and decoupled from that of the individualistic behaviour. The proposed coupling of the social behaviours results in a significantly better mean arrival-time performance and also in reduction of arrival-time uncertainty.

Keywords: bio-inspired, school-of-fish, social behaviours, multi-agent systems, source localization, autonomous agents.

1. INTRODUCTION

Natural multi-agent systems have played an inspirational role in the field of applied engineering research [1, 2]. In the domain of source localization, there are significant number of bio-inspired approaches and methods in the literature [3-5]. Some recent work has focussed on investigating the school-of-fish social behaviours for their ability to benefit a specific agent or a whole team localizing a source [6-8]. Fish are known to find food [9] or acoustic [10] sources in large schools or shoals. Large aggregations of fish show a collective behaviour [11] in the form of swarming, milling or schooling [12] which emerges from very simple social behaviours which benefits a fish in different scenarios, e.g., foraging and evading predators, etc. Social behaviours are dependent on some sort of neighbour information whereas individualistic behaviours are based on agent's independent perception of the environment. Research has identified three social behaviours which form the basis of collective behaviour in a school-of-fish, i.e., the long-range attraction, the short-range repulsion and the neighbour alignment [12, 13]. The three behaviours are dependent on the flow of social information within a school, i.e., the information a fish acquires about its neighbours within a certain neighbourhood. Well-known social behaviour models use either the unit-vector [12] or the centroid [14] based position information.

How the collective behaviour, emerging from the underlying social and individualistic behaviours, will benefit an agent or a team depends on the context of a problem. As far as a source localization problem is concerned, it is mainly the underlying phenomenon of implicit averaging that plays the beneficial role. A recent study [6], investigated the role of the long-range attraction and the short-range repulsion behaviours for a source localization problem. While the study suggests that the long-range attraction behaviour is mainly responsible for more efficient performance of a team, it does not consider the contribution of the neighbour alignment behaviour. In this paper, we include the neighbour alignment behaviour to study the role of the three fundamental social behaviours working together. Moreover, in the recent set of studies [6-8, 15], the long-range attraction behaviour has been coupled with the individualistic behaviour called *source bias* (or target drive) whereas the short-range repulsion model operates at an entirely different and a significantly shorter time scale – imperative for the job of collision avoidance [6, 15]. In this paper, we present a new approach pertaining to the operational time-scales of the social and the individualistic behaviours. We report that the localization performance is significantly improved when the operation of all the social behaviours is coupled together at the same time-scale but decoupled from the individualistic behaviour. To show the generic applicability of the result, we use two different individualistic models, one that is a static source bias model [6, 7] and one that is an adaptive source bias model [15].

2. LOCALIZATION SCENARIO

We assume an acoustic point-source located at the origin of a two-dimensional search plane, position of which is unknown to all the agents. 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 it following the initial entry. Specific arrival helps us substantiate the benefit a certain individual enjoys being in a team as compared to being alone. While a specific arrival scenario [6] holds more biological importance, it is closely related to the last arrival scenario which has been used for engineering related problems [7, 15]. In the case a specific-arrival performance thrives on social behaviours, the last arrival being a more cooperative scenario will thrive even more and hence making the specific arrival a more conservative choice.

3. SIMULATION SETUP

Table 1 shows the parameters assumed for an agent's dynamics which bears close semblance to the fish-

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dynamics model as given in [12] and we use the same symbols where possible for an easy reference. The assumed model also relates well with some miniature mobile robots fabricated at centimeter scale [16]. We use a team size of 20 agents starting within a circular starting zone of radius $1\,\mathrm{m}$, centered $50\,\mathrm{m}$ away from the source. The radius of the success zone is also set to $1\,\mathrm{m}$. An agent only slows down to its minimum speed, s_{min}, when avoiding collisions or after its arrival inside the success zone, otherwise it runs at a constant maximum speed, s_{max}. Contrary to the maximum attraction neighbourhood, r_{a} of $0.75\,\mathrm{m}$ in [12] which is enough to show local swarming behaviours, we set r_{a} to $5\,\mathrm{m}$ because of the requirements on attraction neighbourhood radii as discussed in [6] for a source localization problem while employing a small team. The zone for the neighbour alignment behaviour is commonly known as the orientation zone for which radius, r_{o}, was optimized using a Genetic Algorithm (GA).

Social behaviours, i.e., the long-range attraction, the short-range repulsion and the neighbour alignment, are taken in the same form as given in [12] and hence represent the unit-vector information model as discussed in [6]. Let $\mathbf{d}_{\text{r}}$, $\mathbf{d}_{\text{a}}$ and $\mathbf{d}_{\text{o}}$ be the repulsion, attraction and orientation, direction unit-vectors respectively as described in [12]. Also, let $\mathbf{d}_{\text{ind}}$ be the direction vector dictated by the individualistic behaviour which drives an agent towards the source and is independent of any social information. We choose the source bias model [6] for that purpose where heading of an agent i is given by

$$\mathbf{d}_{\text{ind}_i}(t+T_{\text{ind}}) = \begin{cases} \mathbf{d}_{\text{ind}_i}(t) & \text{if } I(t+T_{\text{ind}}) \geq I(t) \\ R^{+}_{\theta_{\text{c}}}\mathbf{d}_{\text{ind}_i}(t) & \text{if } I(t+T_{\text{ind}}) < I(t) \end{cases} \tag{1}$$

where I is the signal intensity, R^{+} is the counter-clockwise rotation matrix, θ_{c} is the correction angle an agent adds to its previous heading in case it is not going in the direction of increasing acoustic intensity. To generalize the results further, we also use an adaptive version of the individualistic model as given in [15] which changes its sampling time, as a function of the sensed intensity.

Let us define the weighted-average direction vector for an agent i based on the social behaviours (excluding the short-range repulsion) and the individualistic behaviour as

$$\mathbf{d}_{\text{w}_i}(t) = b_{\text{s}}\mathbf{d}_{\text{ind}_i}(t) + (1-b_{\text{s}})\mathbf{d}_{\text{a,o}_i}(t) \tag{2}$$

where $b_{\text{s}} \in [0.5, 1]$ is the source bias coefficient and

$$\mathbf{d}_{\text{a,o}_i}(t) = \begin{cases} \mathbf{d}_{\text{a}_i}(t) & \text{if } n_{\text{o}}(t)=0,\, n_{\text{a}}(t)\neq 0 \\ \mathbf{d}_{\text{o}_i}(t) & \text{if } n_{\text{a}}(t)=0,\, n_{\text{o}}(t)\neq 0 \\ 0 & \text{if } n_{\text{a}}(t)=0,\, n_{\text{o}}(t)=0 \\ \frac{\mathbf{d}_{\text{a}}(t)+\mathbf{d}_{\text{o}}(t)}{\|\mathbf{d}_{\text{a}}(t)+\mathbf{d}_{\text{o}}(t)\|} & \text{otherwise} \end{cases} \tag{3}$$

where n_{a} and n_{o} are the number of neighbours in the zone of attraction and orientation respectively. Note that the higher values of b_{s} mean less team cohesion and vice versa. It needs to be stated that (3) is different from the implementation in [12] where $\mathbf{d}_{\text{a,o}_i}(t) = \mathbf{v}_i(t-\tau)$ in case there are no neighbours in the zone of attraction and orientation, $\mathbf{v}_i$ being the velocity of the agent and τ being the sampling time. However, we find that the performance is significantly better in the source localization setting based on (2) to have zero contribution from $\mathbf{d}_{\text{a,o}_i}(t)$ vector in the case there are no neighbours in both the zones.

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

Sym.	Description	Value(s)
r_{r}	Repulsion radius	15 cm
r_{o}	Orientation radius	$[0, 5]$ m
r_{a}	Attraction radius	5 m
l	Length of an agent	5 cm
s_{max}	Maximum speed	$25\,\mathrm{cm\,s^{-1}}$
s_{min}	Minimum speed	$7.5\,\mathrm{cm\,s^{-1}}$
$\dot{\theta}_{\text{max}}$	Maximum turning rate	$35\,^{\circ}\,\mathrm{s}^{-1}$
σ	Error Standard Deviation	$6°$
α	Field of perception	$360°$
$T_{\text{a,o}}$	Sampling time of attraction and orientation behaviours	$[0.2, 50]$ s
T_{ind}	Sampling time of individualistic behaviour	$[0.2, 50]$ s
T_{r}	Sampling time of short-range repulsion	0.2 s
b_{s}	source bias coefficient	$[0.5, 1.0]$
θ_{c}	Correction angle	$[0, 180°]$

Now, we can write the desired direction of an agent, i, at time, t, as

$$\mathbf{d}_{\text{d}_i}(t) = \begin{cases} \mathbf{d}_{\text{r}_i}(t) & \text{if } n_{\text{r}}(t) \neq 0 \\ \mathbf{d}_{\text{w}_i}(t) & \text{otherwise} \end{cases} \tag{4}$$

where n_{r} is the number of neighbours in the zone of repulsion and the short-range repulsion behaviour operates with the highest priority with a sampling time, T_{r}, which is set to $0.2\,\mathrm{s}$ due to the nature of collision avoidance requirements. Other social direction vectors are updated every $T_{\text{a,o}}$ seconds and the individualistic behaviour is updated every T_{ind} seconds. Both these sampling times have been optimized within a given range as shown in Table 1.

As for the spatial sampling for the source signal, we follow a simple spherical-spreading sound propagation model as given in [17]. For the source, operating at a frequency of $8.8{\pm}1\,\mathrm{kHz}$, we assume a sound pressure level of $180\,\mathrm{dB}$ re 1 μPa at $1\,\mathrm{m}$. The source level corresponds to the sound levels of many commercially available underwater locator beacons. For the ambient noise, we assume a noise level of $118\,\mathrm{dB}$ re 1 μPa in a bandwidth of $2\,\mathrm{kHz}$ which corresponds to the scenario of shallow waters with biological noise [18].

Table 2: Optimal parameters and arrival-time performance of static and adaptive individualistic models operating at the coupled (C) or decoupled (D) time-scales with the social behaviours. Inactive neighbour alignment behaviour is represented as -O and active is represented as +O. The mean arrival time represents average of 49 152 simulation runs.

Sampling	Settings	b_s	θ_c (°)	$T_{a,o}$ (s)	T_{ind} (s)	r_o (m)	mean arrival time (s)
Static	-O, C	0.98	136.40	24.80	24.80	–	1060.30
	-O, D	0.60	141.50	0.20	28.60	–	792.60
	+O, D	0.55	141.50	0.20	29.80	1.39	735.10
Adaptive	-O, C	0.95	93.39	39.40	39.40	–	717.90
	-O, D	0.63	132.92	0.20	47.53	–	594.30
	+O, D	0.59	130.63	0.20	44.41	1.22	572.30

4. RESULTS & DISCUSSION

4.1. Operational Time Scales

Let us first discuss the comparative results of having the long-range attraction behaviour and the individualistic behaviour having a coupled operation at the same time-scales versus a decoupled operation at independent time scales. For the coupled operation as given in the earlier studies, the optimal solution shows virtually no signs of schooling as $b_s = 0.98$ in the first row of Table 2 for a mean arrival time of 1060.30 s over $49\,152$ simulated missions. As we decouple the two behaviours and let both the sampling times, $T_{a,o}$ and T_{ind} be optimized through the GA, we see that the optimal time for the long-range attraction behaviour reduces to 0.2 s, the time scale at which the short-range repulsion behaviour is operating. We also fixed T_r to values other than 0.2 s, i.e., in the range $[0.2, 1]$ s, and every time the optimal $T_{a,o}$ equalled T_r. Compared to the coupled case, we see improvement in the mean arrival-time performance of about $25\,\%$[1] where mean arrival time is 792.60 s (see the second row of Table 2). Figure 1 shows the comparative box and whisker plots where each plot represents $49\,152$ simulation runs (see figure's caption for more details). The figure shows a significant decrease in the uncertainty of arrivals for the decoupled approach as compared to the coupled approach.

For the adaptive sampling based individualistic model, we see the same relative trend for the optimal sampling times when we compare the coupled and the decoupled approaches (see the fourth and the fifth row of Table 2). We can see improvement in mean arrival-time performance of about $17\,\%$[1] when we compare the coupled time-scale operation (717.90 s) versus the decoupled time-scale operation (594.30 s). Accordingly, we see in Fig. 1, the uncertainty of arrivals has been reduced significantly for the decoupled approach which agrees with the results of the static individualistic model.

4.2. Role of Neighbour Alignment

The empirical observations that hint towards the possibility of the neighbour alignment behaviour being an emergent property, i.e., a consequence of the long-range attraction and the short-range repulsion behaviours, are discussed in detail in [6]. Scientific investigations, explicitly targeting source localization problems, also suggest that the neighbour alignment behaviour may emerge from the long-range attraction and the short-range repulsion phenomenon given some cue-following [19]. In this paper, we investigate how much of a performance difference an explicit neighbour alignment can yield in a source localization problem. For the decoupled static individualistic model, we see in the third row of Table 2 that adding the neighbour alignment does improve the mean arrival-time performance (735.10 s) by $7.3\,\%$[1] over the case where the neighbour alignment is inactive (792.60 s). Similarly, Fig. 1 shows reduced arrival uncertainty for the active neighbour alignment behaviour versus the inactive case.

As for the decoupled adaptive individualistic model, we see a mean arrival-time performance improvement of about $3.70\,\%$[1] when we compare the case of active neighbour alignment behaviour (594.30 s) versus the inactive one (572.30 s). The uncertainty of arrivals seems marginally better for the active neighbour alignment behaviour.

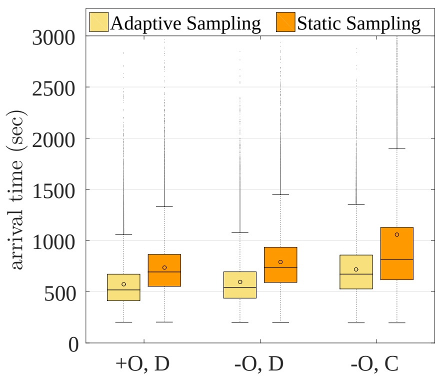

Fig. 1: Box and whisker plots for the performance of static and adaptive individualistic models operating at the coupled (C) or decoupled (D) time-scales with the social behaviours. Inactive neighbour alignment behaviour is represented as -O and active is represented as +O. Each plot represents $49\,152$ simulation runs, a box delineating the 25th to the 75th percentile, the whiskers show the lowest datum still within 1.5 Inter Quartile Range (IQR) of the lower quartile, and the highest datum still within 1.5 IQR of the upper quartile. Circle represents the mean and band represents the median of a distribution.

[1]Performance comparison is significant based on the Mann-Whitney U test for $p < 0.01$.

4.3. Optimal Schooling Behaviour

In all the relative cases discussed so far, if we see the optimal schooling parameters given in Table 2, they show a certain trend. For both the individualistic models, if the performance gets better for a particular approach then the schooling also increases (lower values of source bias coefficient, b_s). For example, with all the social behaviours operating at the same time-scales, the performance is the best and also the value of b_s is the lowest. This phenomenon shows that coupling all the social behaviours together but decoupled from the individualistic behaviours results in improved multi-agent performance by extracting more benefit from the schooling behaviour.

5. CONCLUDING REMARKS

We investigated the optimal operational time-scales for school-of-fish social behaviours, i.e., the long-range attraction, short-range repulsion and the neighbour alignment, considering a source localization problem. For two different individualistic behaviours, our results showed that the social behaviours work significantly better when their operation is coupled together at the same time-scale and decoupled from the individualistic behaviour. The proposed coupling of the social behaviours, not only results in significantly better mean arrival-time performance but also in reducing the arrival-time uncertainty. This time-scale independent property of social behaviours from the individualistic behaviours significantly reduces the complexity of designing a multi-agent system. The social behaviours can be added to already tuned individualistic behaviour(s) to enhance the system's performance by invoking collective behaviour in the team.

The improvement in localization performance due to the neighbour alignment behaviour is significant but the magnitude of improvement is dependent on the type of individualistic behaviour. As more adaptive behaviours are investigated in future, it will become clearer if the neighbour alignment behaviour is indeed an emergent property or an explicit behaviour having a direct contribution towards finding sources of interest.

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