A Bat Social call inspired Algorithm for Multi-Agent Foraging

Mustafa Jamshidpour (jamshidpour.mustafa@gmail.com)
Mehdi Sadeghzadeh

Short Report

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A Bat Social call inspired Algorithm for Multi-Agent Foraging

Mustafa Jamshidpour[1*] and Mehdi Sadeghzadeh[2†]

[1*]Department of Computer Engineering, Islamic Azad University, Bushehr.
[2]Department of Computer Engineering, Islamic Azad University, Mahshahr.

*Corresponding author(s). E-mail(s): jamshidpour.mustafa@gmail.com;
Contributing authors: sadeghzadeh1999@gmail.com;
†These authors contributed equally to this work.

Abstract

This paper proposes a new method to solve the problem of foraging in swarm robotics. This research approach is inspired by the collective behaviours of some species of bats that communicate the location of food or nests to other group using sound signals. A mechanism has been established a mechanism for more effective communication between agents. Within the framework of a self-organizing system without a central controller and through coordination mechanisms in individuals, we propose a way to prevent overcrowding at the point of exploitation and continue exploration. In this research, homogeneous agents, independently, with limited perception and processing ability, can determine and change their role in the group, and according to their role, they perform various tasks and cooperate and interact with other agents, and change and determine the roles of the agents according to rules, social or threshold time is done according to a probabilistic model. We tested the proposed method in a simulation environment and showed the performance of a group of individual agents with minimal cognitive and processing abilities.

Keywords: Foraging;Swarm robotics;Swarm intelligence;Self-organization;Multi Agent system

1 Introduction

This research focuses specifically on presenting and analysing an optimal solution to the problem of foraging. The main goal of this paper was to create a minimal foraging model that could dynamically adapt to the unknown environment. This study aims to use the social behaviour of bats to design a new algorithm to increase energy efficiency and reduce downtime.

Foraging is a fundamental issue for swarm robotics research[1][2], reasons for this importance are that foraging is a complex process that involves several tasks of compelling exploration for target objects, physical collection, and then their transfer to the nest[3]. Practical applications of this type of task include collect hazardous waste, planetary exploration,rescue operations in accident-hit buildings, industrial and non-industrial applications that require joint work, construction, transportation, inspection, maintenance and monitoring of the environment[4][5].

Foraging is the act of searching and gathering food or prey borrowed from biological systems. Ants and other social animals can access food resources using local interactions between individuals[6]. This task describes a multi-agent system where agents individually and autonomously search for objects called "food" in an unknown environment. Agents move and search randomly, and after finding it, they bring objects to an area called a "home" and share the food source location information with other agents[7]. This task is more complex than searching for pure exploration, delivering, and saving target objects. To do this, agents must have special abilities such as navigation, food and obstacle detection, and the ability to find their way back to the nest. If a single agent has enough time, he or she may accomplish this task, but a group of agents who work together can do this much faster with less effort due to collective participation[8].

Swarm intelligence studies the behaviour of entities that lack a central controller, a set of individual components that are independent in their actions and are able to interact with the environment and enter into partnership with other components to achieve a common goal[9]. The intelligent behaviour of the group is created through the pattern of the organization itself[10]. The system itself is dynamic, meaning that the components constantly change relative to each other. Changes are initially local, and the components communicate only with their immediate neighbours. They are practically independent of the more distant components however, self-organization is often defined as the emerging public order of local interactions [11]. Four essential characteristics of positive feedback, negative feedback, fluctuations, and multiple interactions on which self-organization takes place have been identified[12].

This research examines a decentralized solution to information sharing and coordination between agents. In this proposed method, the agent that has reached the food site earlier than the others plays an intermediary role in attracting other agents by emitting sound signals. To avoid overcrowding at the food or nest site, an algorithm that can strike the optimal balance

between exploration and exploitation has been proposed.
The collective behaviours of animals in nature are often used in swarm robotics[13]. The biological basis of this approach has inspired social calls in bats, which biologists have recently considered. The nocturnal activity of bats and their desire to live in a particular range has highlighted the role of audio signals in contrast to various communication methods such as visual signals, and it can be said that bat audio signals optimize transmission according to the environment[14].
Audio signals such as pheromone can bypass obstacles and propagate in different temporal and spatial situations; and duration and frequency are effective in transmitting the information. Other signal transmission features, such as transmitter positioning, also make it more important to use. Variety in animal communication systems demonstrates the importance of signals in various behavioural interactions. Sound can be adapted to various environmental conditions and behavioural situations[15]. Acoustic communication allows efficient information exchange between sender and receiver[16]. Aspects of the contact structure, such as amplitude, duration, and frequency, affect other signal transmission characteristics, such as distance travelled in the environment and the ability to localize the transmitter position. Studies show that bats use two types of echolocation and social calls in communication[14]. Due to their low frequency, social signals can be used at longer distances than echolocation signals. Downstairs, they bring their roommates with them. This call can travel farther than echolocation and transmit more information. Selective experiments have shown that flying bats respond preferentially to calls from members of the same group, but barnacles or emerging bats respond to any contact without distinction[17]. Bats that use rich, very fleeting pieces of insects will benefit most from eavesdropping because the presence of multiple bats feeding in one area will not reduce a person's search for food [18]. Very little signal information there are bats used to communicate about food. Calls for recruitment and coordination can be linked to food exploration or exploitation.[19].

2 Releated Works

The social behaviour of ants has inspired further research on foraging. In ant-inspired foraging research, pheromone distribute information and build collective memory[20]. Although the pheromone is easy to use in simulated systems, it is not easy to find a suitable alternative for real-world application. This synthetic pheromone is only effective in controlled environments such as a factory. In the absence of such objects, pheromone trials must be simulated by a central controller or the agent[21]. This research has three main approaches to emulate ant pheromones: beacon robots, physical materials, and virtual pheromone.[22] This puts high computational pressure on the distributed system, thus limiting its scalability and usability.

Since foraging is a multi-stage process, various research mechanisms have been developed for tasks allocation[23]. Studies that are more similar to our research and the ideas we have got from them are mentioned here.
[24] Propose two decentralized algorithms, robots that act as beacons are used for the virtual pheromone. Pheromone are stored in beacon robots and are transmitted to other nearby robots by them. Robots can also decide whether to act as a beacon, or a walker.[25] Presented an ant-like division of task model, in which, heterogeneous agents behave like three species of larvae, searcher, and transporter. Environmental changes can increase the number of agents in one task or decrease them in another. The threshold function of the system is divided into two parts. The first is to determine the order of tasks and the second checks if the amount of food in the nest dock decreases.
[26] Propose an algorithm which is a free, distributed and heterogeneous parameter version of the wavefront algorithm. [27] Presented a foraging model in which each agent provides information to other agents about success in finding food in a certain radius, and agents that have not been successful in their search for food either continue to search or move towards that agent .
[28] Present a study that uses only the rate encounters of agents instead of using pheromone trails to create common collective behaviours. This mechanism creates an interactive network that, in addition to accessing and retrieving food, balances traffic on different routes completely decentralized.
[29] Inspiration by honey bee colonies has developed a method for searching and retrieving food based on the partitions in the search space, and assigns various behavioural roles assigned to the agents. [30] Introduce a task allocation model of the concept of traffic flow density, which can be used to reflect the traffic condition in the foraging area. The value of obstacle avoidance adjusts the threshold value so that the individual robot can independently determine whether to search for forage or not. The authors have shown that this model improves the threshold of forage search efficiency.
[31] To optimize the balance between the number of robots assigned to a task and the overcrowding of robots in a technical area, suggest that each robot use only binary information and about the presence of other robots around it to estimate congestion density and decide whether to stay and continue an assigned task or voluntarily leave the area. Demonstrating this technique can increase the overall efficiency of the system.
[32] Develop an algorithm for controlling swarm robots that adjusts their turn probability based on the attraction and repulsion signals they sense from other robots.

3 Description of the Approach

This paper aims to design a new coordination mechanism for collecting target objects by a group of very simple robots. Homogeneous agents with limited sensory and communication capabilities and memory can not store route

information. They can only sense the target at a certain distance. An agent can receive information only from those robots within its communication radius. Their transmitted signal contains only two types of information: near the nest or the food site, and other agents can only estimate the direction and intensity of the received signal by eavesdropping. Agents have no information about their position or the position of other agents. The speed of the agents is constant and far less than that communication signal. The agent can send a signal on the move or at rest. Each robot acts independently only based on current measurement data and has no central controller to guide. There are no agents and location information or available or collected amount of food.

3.1 Environmental Model

The environment model in this research is a lattice square defined in two layers. The first layer organized layer is search space as $N \times N$ grid that contains nest (Home) location, obstacles, and several food sites. The nest is the initial position and ending point of agents movement and is located in the centre of the environment. There is some food on each site. The number of sites and the total food available for collection in the environment can be changed as a parameter in different scenarios. Obstacles with circular shapes take place on some random cells. The environment can be obstacle-free. Cellular automation is a tool for modelling complex systems. We have simulated the physical properties of sound propagation in the environment using the proposed model of [33] and [34] in the second layer of the simulation environment.

3.2 Agent's Mechanism

The mechanism of agents is designed based on the InteRRap architecture. The upper layer, which is related to the social interactions of agents, is introduced as roles. The second layer, related to planning to achieve goals, in this proposed method is introduced as Figure 1 shows.

3.2.1 Roles Layer

The role layer in the proposed algorithm has been used to overcome the complexity of foraging jobs and to use task allocation with homogeneous agents. Roles are sub-goals that agents seek to achieve in this study, and they have the following four characteristics: protocols, which define specific patterns of interaction with each other; activities, tasks related to the role that the agent performs without or with interacting it; permissions that specify access to information resources; and finally the responsibilities[35].
The role of each agent is an internal state that changes according to environmental or internal conditions. By finding food, the agent becomes the caller, and after inviting other agents, he takes the carrier role. when the carrier finds a nest, it takes on the role of caller again and then stays in the nest or

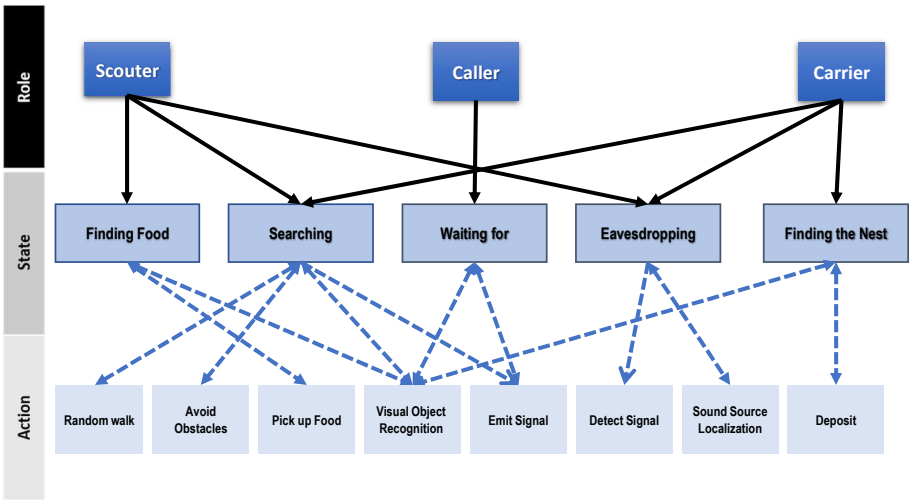

Fig. 1 Agent design model in the proposed method.

searches for food, depending on the environment.

3.2.2 States

Each agent has one or more different modes in the role it assumes. Each state is a set of environmental perceptions, logical rules, and actions that shape agent behaviour. Agent programming is done at this level. Five modes for agent behaviour are considered in this study:
1. Searching
1. Finding food
3. Waiting
4. Eavesdropping
5. Finding the nest
Figure 2 shows the finite state machine for modes and conditions of state change. Each state represents a behaviour, and each is a set of discrete actions. To control the agent's behaviour, it uses the environmental conditions of the social conditions described in the Coordination Mechanism section and the time variables, which increase in each runtime cycle to reach the threshold, then the agent switches to another mode. The time variables are reset in the

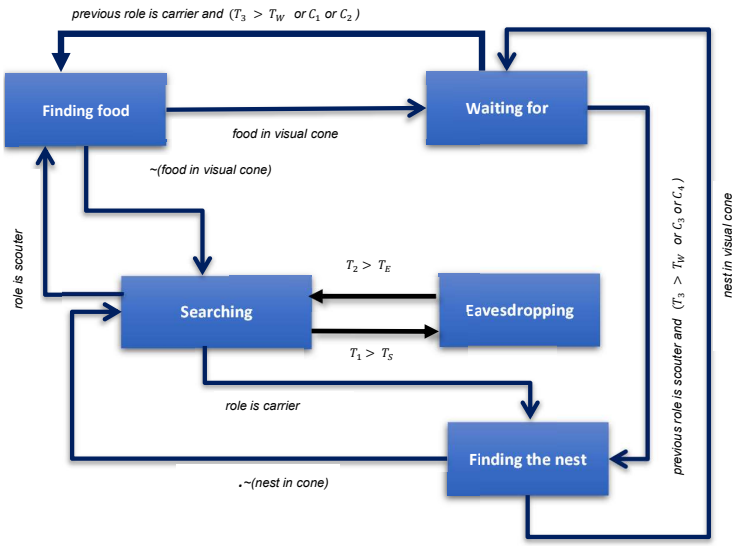

Fig. 2 Finite state machine of the proposed system.
T_S: Threshold for Searching .T_E: Threshold for Eavesdropping.
T_H: Threshold for Homing. T_W:Threshold for Waiting.

new state until the next state's conditions are met. The nest is the starting and ending point of travelling for each agent. The agent exits the nest if food is not seen in a visual cone area V_r; it randomly walks around the environment to find the food or to receive attractive signals indicating the location of the food. When the food site is in the field of view, it goes straight to it and picks up a piece of food according to its capacity, emits an audio signal, signalling the location of the food to other agents after the waiting time delay, the agent randomly searches for the nest.

3.2.3 Searching

In this state, the agent searches the food site or nest. This state includes walks based on random walks method, avoidances obstacles, and moves directly to food and nest sites. If the total search time of the agent in the environment T_4 is greater than the threshold T_H and food is not found, it returns to the nest in the role of the carrier.
Another action that the agent performs, in this case, is the propagation of sound waves near the food site and participation in cooperation clusters to

amplify the signals received from other agents to do this, a T_3 with the T_E threshold determines the propagation duration time.

3.2.4 Finding Food

When the food is in the visible range of the agent, it moves directly to the piece with the highest amount of food. After reaching the target point, it makes sure that the food is present again (because the adjacent agents may have reached the target earlier). Absent at the target point again finds the role of scouter.

3.2.5 Waiting

This mode is suggested for the role of the caller. Inspired by the collective behaviour of some species of bats, and to make more use of the food site, the agent does not return directly to the nest after reaching the food site, nor does it rest or search again when it reaches the nest and food site. This case is under the coordination mechanism described in the next section, which helps create or strengthen cooperation clusters.

3.2.6 Eavesdropping

Another behaviour of bats is modelled in this proposed method, eavesdropping. Agents listen to signals emitted in the environment by controlling T_1 and T_2. Suppose there is a strong signal in the environment. In that case, they compare the received signal with the signal strength they have in memory and according to the communication mechanism described in the next section. Through the gradient algorithm, the signal intensity in the environment can be adjusted to move to the nest or food site.

3.2.7 Finding Nest

The agent approaches the nest by randomly searching or following the signals sent by other agents from the nest and moves directly towards the nest if it is seen.

3.3 Communication Mechanism

Agents begin to emit sound waves as they settle in the nest or food site. This propagation of signals continues for a limited time after leaving the location. The duration of propagation of signals depends on the coordination mechanism, which will be described in the next section.
Mobile agents eavesdropping on peripheral signals are distinguished in three zones according to the intensity of the received signal.
Zone 1: Close distance: in this zone, the location of the emission source is precisely identical to the agent, so the agent moves towards it with the slightest deviation in the angle of motion.
Zone 2: Medium distance: in this zone, the agent's role is to cooperate with the

primary signal propagating agent to create a cooperative cluster and retransmit the signal. The signal receiving agent, according to formula 1 specifies the propagation rate and amplitude of the signal. The agent compares the new signal with the one it has in memory. If this new signal is greater than the value in memory, it moves through the gradient descent algorithm to the signal source. Otherwise, it changes direction 180 degrees. This mechanism causes other nearby agents to be directed in clusters to the nest or food site.
Zone 3: Far distance, although the received signal is detectable, due to the long distance, the position of the signal source is not detectable for the agent, and receiving the signal does not change the direction of the agent.
In this research, a coefficient called α_i is used to adjust the propagation rate and amplitude of the transmitted signal, which is $0 \leq \alpha_i \leq 1$. For each agent in the second zone, we have:

$$\alpha_i = \frac{A_{max} - A_i}{A_{max} - A_{min}} \tag{1}$$

Where A_{max} is the maximum signal amplitude, A_i shows the received signal amplitude, and A_{min} refers the minimum signal amplitude [36][37]. And the transmitted signal is :

$$\hat{A}_i = A_{max}(1 - e^{\alpha_i}) \tag{2}$$

The agent compares the intensity of the received signal in two steps. If the difference between the intensity of the previous signal and the current signal was greater than zero, it reduces its turn angle and moves directly to the newly received signal. If this difference is less than zero, the agent then turns its heading 180 degrees.

3.4 Coordination Mechanism

In addition to effective communication, the second important factor in the foraging job is the mechanism of cooperation. This mechanism should be an optimal trade-off between the energy consumed and the amount of food collected. In this proposed algorithm, the agents that waited at the nest or food site begin to send signals to attract other agents; with a long waiting time, more agents accumulate in one place and, in addition, the time of food transfer to the nest. Increase to avoid over-accumulation of agents at one point and to accelerate the activity of returning to the nest or re-searching for food, and we have provided a mechanism that can create a balance between new exploration and exploitation without a central controller.
Hence, the rules of waiting are as follows:
C1. If food is not available on the site, the agent leaves the site.
C2. If the number of visible neighbour agents is greater than 2, the agent will leave the food site with a $\frac{n}{8}$ probability.
This rule states that the duration of the waiting is an inverse ratio to the number of neighbouring agents and that increasing the partner increases the likelihood that the agent will leave the group.

C3. If the agent is in the nest and the total travel time of the agent is greater than the maximum travel time defined, it remains in the nest.
C4. If the agent is in the nest and the trend of changes of visible agents P according to the formula is greater than 3, it will not stay in the nest.

$$P = \sum_{1}^{SuspendTime} sgn(x_i, x_{i-1}) \tag{3}$$

That

$$sgn(x_i, x_{i-1}) = \begin{cases} 1 & x_i > x_{i-1} \\ -1 & x_i \leq x_{i-1} \end{cases} \tag{4}$$

Where x_i is the number of adjacent agents that are visible to the agent in cycle i.
C5 - To avoid excessive resonance of signals sent from a food site or nest, the emission rate of each agent is adjusted relative to the neighboring factors n.

$$\gamma_i = \frac{1}{n_i} \tag{5}$$

4 Simulation and Experimental Results

We tested our algorithm to demonstrate the agent's ability to explorer the environment, find food and make a proximity optimal path between nest and food sites. Implementation is done in the NetLogo simulation. Figure **??** shows the system in time cycle 10-2000. The environment in all experiments is a 100×100 grid. The nest is located in the centre, and three food sites are also considered in the model. Experiments were repeated 10 times for each scenario and averaged results are reported. At every time step, we log data about each agent: Role, food that carried and position additional, timestamps of agents leaving the nest or food site are event logged for our analysis.
The value of model parameters used in the experiments are listed in Table 1. Figure 4 shows the changes in the role of agents in the three modes of scouter, carrier, and caller, the initial role of all agents are scouter, so the general trend of changes in this role is descending, positive changes in the range of 200 to 1200 steps indicate that this role alternates symmetrically with that of the carrier, which indicates a change of role after finding food and after transferring it to the nest again to play the role of scouter, from 1600 steps until the end of the simulation time, the number of scouts will decrease to zero. From 1900 steps, only a few limited carriers will remain on the outside nest, and the rest of the agents will play a caller role.

4.1 Performance Metric

We have used the performance indicators used by [8][38][39] that include a set of comprehensive criteria for evaluating foraging models. These criteria include

Table 1 Agent and Environment Parameters

Parameters	Value	Description
N_a	30-100 units	Number of Agents
V_r	120°	View Angle of Camera
R_a	4cells	Camera Detection Range
σ	U(-π/4,π/4)	Angle Random Walk
E_c	1units	Energy Consume per tick
A_{max}	0.9	Maximum Signal Amplitude
A_{min}	0.1	Minimum Signal Amplitude
T_S	10-30ticks	Threshold for Searching
T_E	10-30ticks	Threshold for Eavesdropping
T_H	3000ticks	Threshold for Homing
T_W	10-30ticks	Threshold for Waiting
ΔT	0.5sec	Time Step Duration
F_S	1-3sites	Food Sites

Total Food Returned, Total Energy Consumed, Energy efficiency,Energy efficiency in time and Total foraging time, which is defined below:

Definition 1 The total amount of food returned over time is called Total Food Returned.

Definition 2 The total energy consumed in the total energy expended by all agents to search for and transport nutrients to the nest.
This index is equivalent to the path taken by the agents from the beginning to the end of simulation time.

Definition 3 Energy efficiency E_{eff} is the average energy consumed to collect food calculated according to (6). Since the total energy consumption increases with time, if $E_{eff1} < E_{eff2}$ so E_{eff1} is better.

$$E_{eff} = \frac{Total\ Energy\ Consumes}{Total\ Food\ Returned} \tag{6}$$

Definition 4 Energy efficiency in time (E_{efft}) is the average energy consumed up to time t to collect food is up to time t and is calculated according to (7).

$$E_{efft} = \frac{Total\ Energy\ Consumes(t)}{Total\ Food\ Returned(t)} \tag{7}$$

Definition 5 The time required to complete the search mission is called Total foraging time ($T_{foraging}$).

Figure 5 shows the changes in distance travelled or the energy consumed, as well as the amount of food collected. This diagram shows that the motor changes of the agents are used to increase the amount of food collected. Figure 6 shows that the energy efficiency of the model remained at a constant level

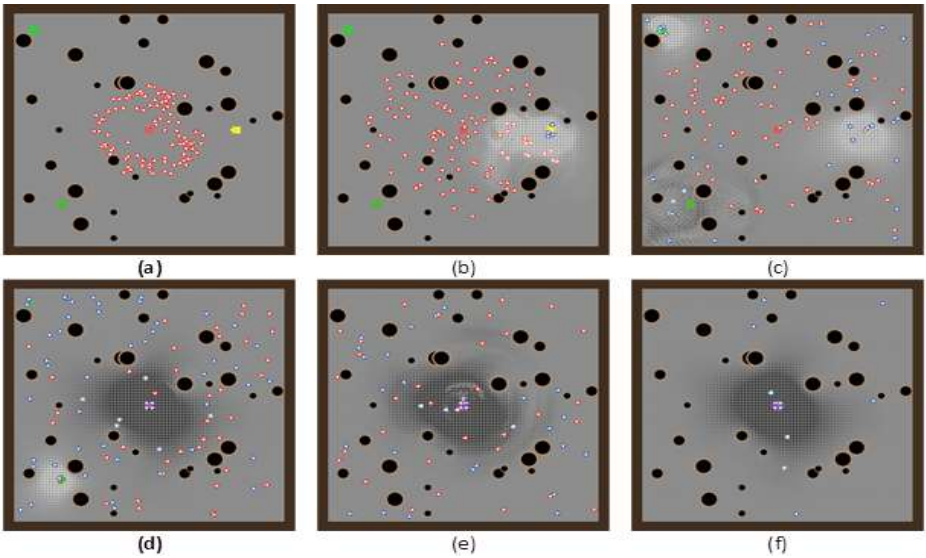

Fig. 3 Display of the position of agents in the simulation.
a: cycle 10, agents search in the environment randomly.
b: cycle 20, agents find the food site and propagate the signal.
c: cycle 100, agents find all food sites.
d: cycle 300, the collection of all food from site one and bringing it to the nest.
e: cycle 1000, the withdrawal of all food from sites 1, 2, and 3.
f: cycle 1980, all agents return to the nest.

after some time from the start of work; in other words, the work done to collect was proportional to the food stored in the nest.

4.2 Scenario 1:Effect of Cooperation of Agents on Improving Efficiency

This test is designed to prove the main goal of this research. For this evaluation, for several agents from 20 to 150 with the unobstructed environment and environment with barriers and each test was performed with 10 repetitions for 2 scenarios.
In the first scenario, there is no signal transmission and cooperation between agents. Each agent individually returns to the nest after searching in the environment if it finds food, and in the second scenario, according to the proposed algorithm, the task of searching is performed by communication, cooperation and coordination between the agents, time to find, transport and store a food unit.

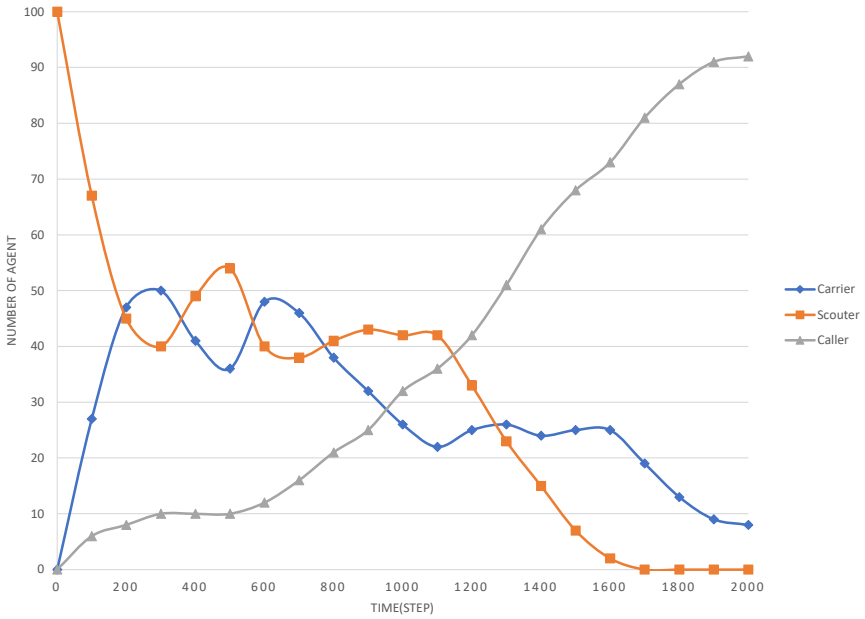

Fig. 4 Changes in the roles of agents.

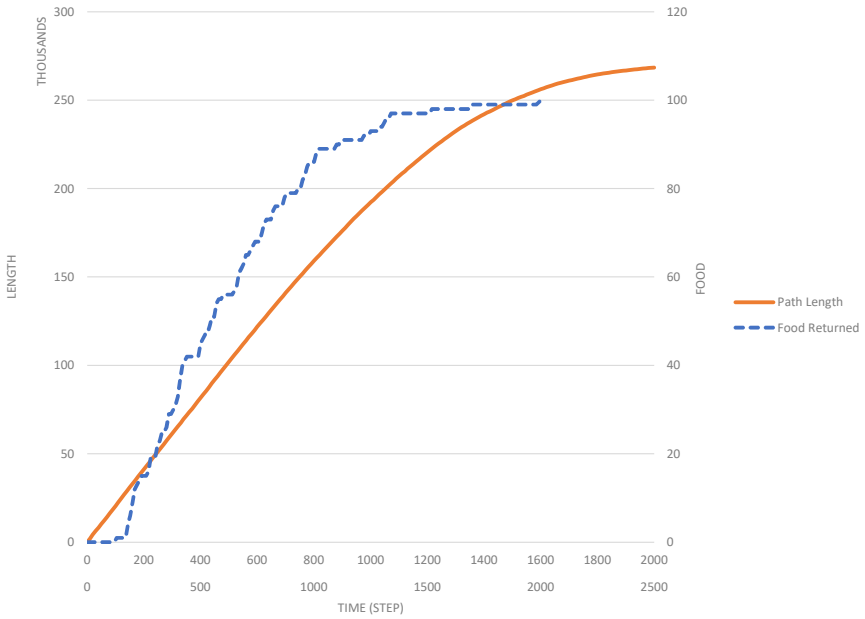

Fig. 5 Changes in distance travelled and food stored.

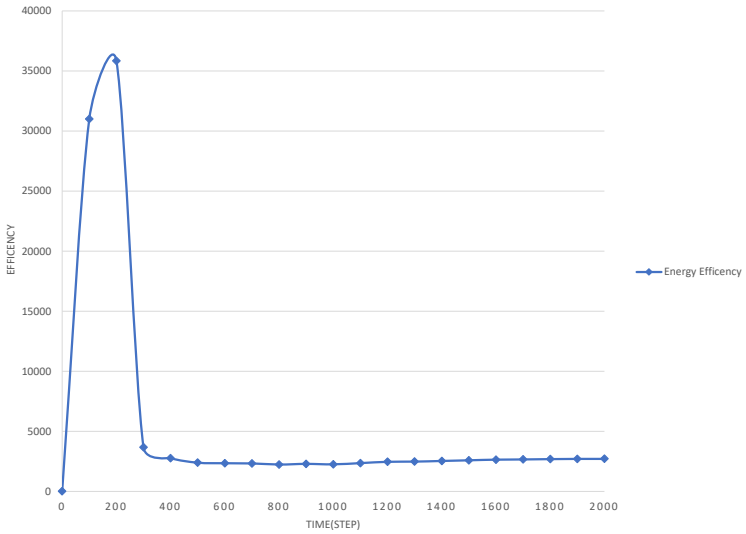

Fig. 6 Changes in energy efficiency during foraging.

Table 2 Comparison of energy efficiency and acquisition time in shared mode

Number of agents	No obstacle		With obstacle		Average	
	energy efficiency	Access time	energy efficiency	Access time	energy efficiency	Access time
20	820	39	1.559	71	1.190	55
30	1045	28	1.724	49	1.384	38
40	1.210	21	1.880	40	1.503	29
50	1.330	17	1.984	34	1.657	26
60	1.493	15	2.083	30	1.805	23
70	1.570	13	2.371	28	1.970	21
80	1.676	13	2.588	30	2.097	20
90	1.727	10	2.928	29	2.328	20
100	1.920	11	2.868	25	2.335	17
110	2.053	10	3.023	22	2.477	15
120	2.119	10	3.257	24	2.688	17
130	2.310	10	3.489	23	2.865	16
140	2.492	10	3.690	21	3.016	15
150	2.477	9	4.006	25	3.286	17
Average	1.744	15	2.675	32	2.193	23

4.3 Scenario 2: Effect of number food sites

In this scenario, the effect of dispersion and food sites on foraging time and energy efficiency has been investigated. The experiment was evaluated for one to three food sites with and without obstacles. The final condition is to reach 3000 steps or complete collection (100 units) of food in the environment. Table 4 shows the test results. It can also be seen that with an increase in the number of food sites, the average foraging has reached almost one-third and the average energy efficiency has been halved. They move between the position

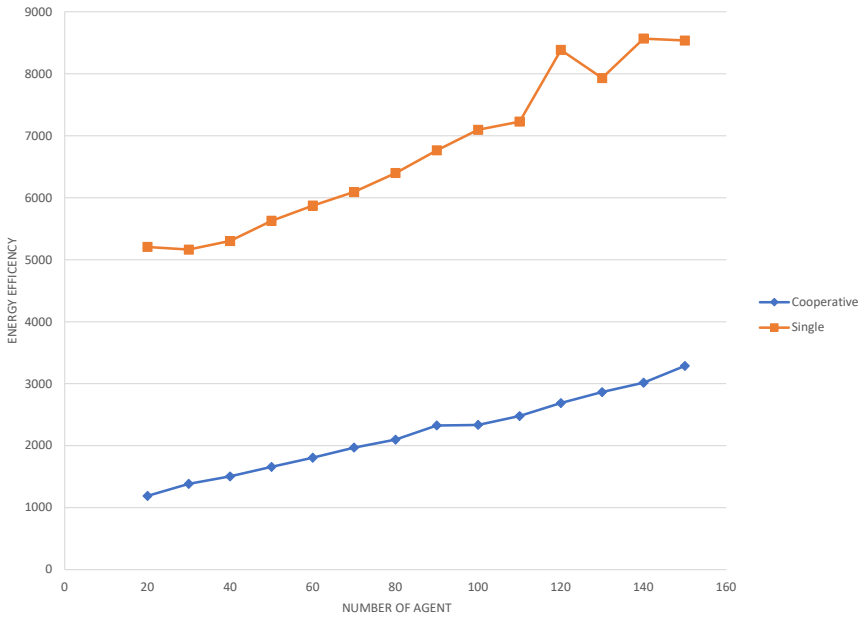

Fig. 7 Comparison of energy efficiency in two modes of individual and shared performance.

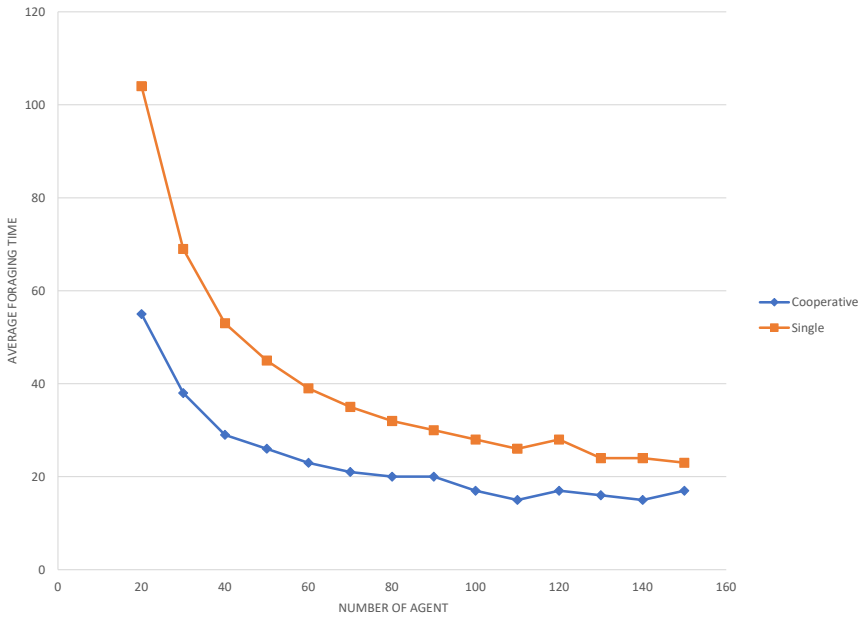

Fig. 8 Comparison of access time of individual and shared performance modes.

Table 3 Comparison of energy efficiency and achievement time in individual mode

Number of agents	No obstacle		With obstacle		Average	
	energy efficiency	Access time	energy efficiency	Access time	energy efficiency	Access time
20	5.149	103	5.262	105	5.205	104
30	4.816	64	5.510	74	5.163	69
40	5.890	49	5.717	57	5.303	53
50	5.371	43	5.884	47	5.627	45
60	5.486	37	6.260	42	5.873	39
70	5.958	34	6.226	36	6.092	35
80	5.700	29	7.098	36	6.399	32
90	6.336	28	7.194	32	6.765	30
100	6.562	26	7.632	31	7.097	28
110	6.554	24	7.901	29	7.277	26
120	7.628	25	9.140	30	8.384	28
130	7.582	23	8.282	25	7.932	24
140	7.874	23	6.262	26	8.568	24
150	7.464	20	9.611	26	8.538	23
Average	6.241	38	7.213	43	6.727	40

and the nest. The reduction in time and energy efficiency occurs because as the number of food sites increases, the probability of finding food for the swarm agents increases.

Table 4 Effect of number of food sites on the time and energy efficiency of the model

	No obstacle		With obstacle		Average	
Number of food sites	Time to collect a unit of food	energy efficiency	Time to collect a unit of food	energy efficiency	Time to collect a unit of food	energy efficiency
1	16	2.663	80	5.847	54	4.286
2	13	2.072	31	3.156	23	2.635
3	12	1.925	27	2.984	19	2.402
	17	2.120	47	4.036	32	3.111

4.4 Scenario 3: Scalability

In this test, the effect of the number of agents on the efficiency of the algorithm is investigated. The test was performed for 30 to 150 agents in each run with ten repetitions and in two modes with and without obstacles. Two sub-scenarios have been considered for this study. The first scenario involves fixed time steps for several different agents and the second one involves the total distance travelled or the total energy consumed.

Sub-Scenario 1: The run time is 1000 steps for all modes. In Figure 9, the amount of food collected has an upward trend from 30 to 80, and it can be concluded that for a limited time, at least 80 agents are needed to collect food

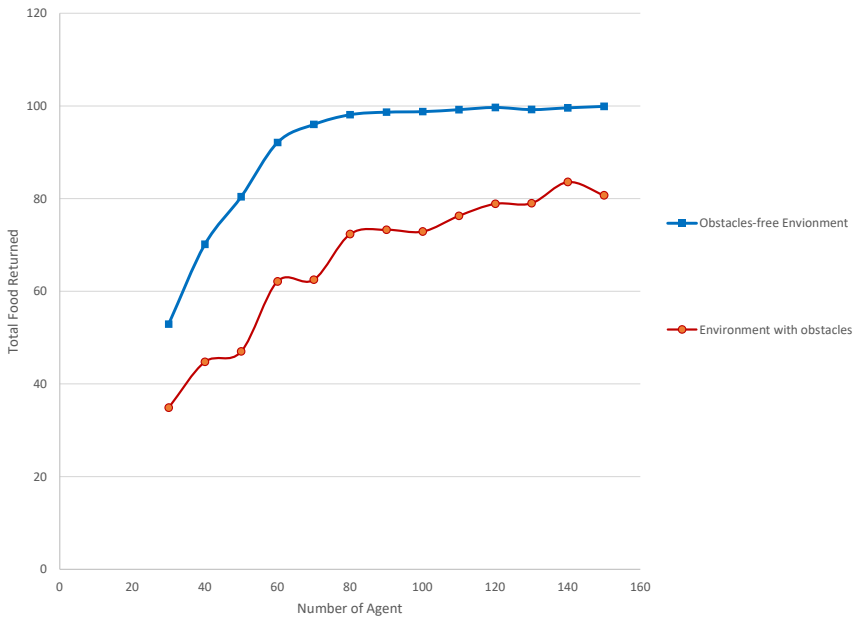

Fig. 9 Effect of agent number on the number of food collected at a fixed time

up to the amount in the environment. This diagram also shows that increasing the number of agents had almost no effect the amount of food collected.

Sub-Scenario 2: In this scenario, we have assumed that the total energy consumption of the agents is $100,000$ units, with the assumption that the simulation has been executed for several different agents. Figure 10 shows that increasing the number of agents does not increase the amount of food collected when the amount of energy is limited. On the contrary, it has reduced the number of foods collected.

4.5 Scenario 4: General Behavior

This examination investigates the convergence of our algorithm and shows the model acts like a self-organizing system whose general behaviour stabilizes after a limited time. In this test, 100 food units with 100 agents have been tested. The number of repetitions is ten times, and the maximum time is 3000 cycles. The system behaviour is recorded for each performance in ten-time sections, and finally, the average behaviours are measured. Figure 11 shows the amount of food collected, the amount of food stored in the nest, and the amount of food available to carriers that should be in the nest. As shown in the diagram, after one-third of the time, the total amount of food collected and the remaining food reaches a balanced state, and the number of agents that carry the food and have not yet reached the nest is reduced to zero. As Figure 11 shows, from the time of 1000, i.e. after $\frac{1}{3}$ of the total time, the

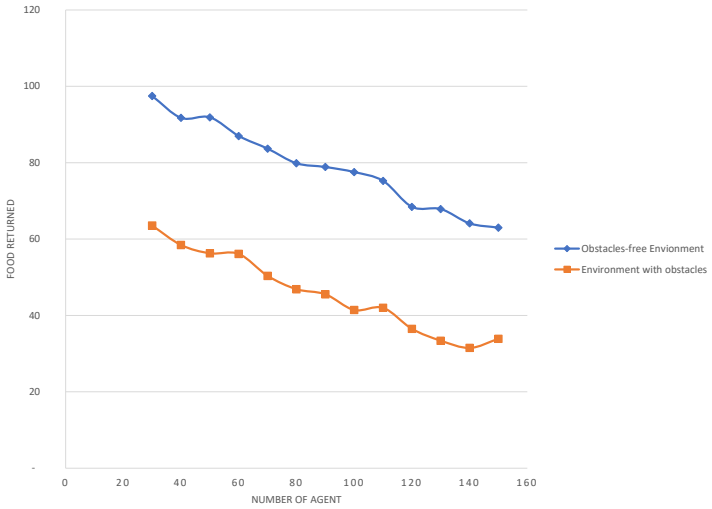

Fig. 10 Effect of the number of agents on the number of food collected for total constant energy

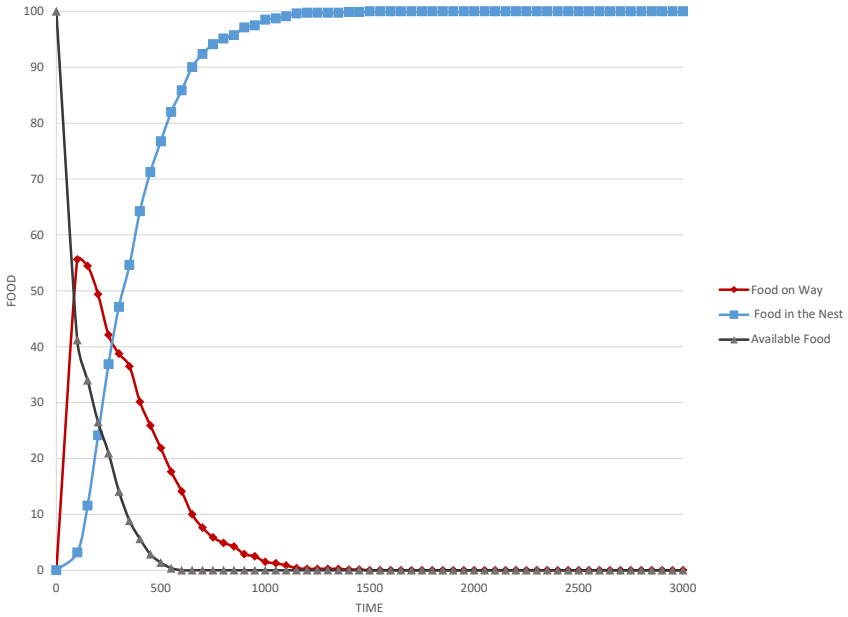

Fig. 11 Convergence of the proposed algorithm

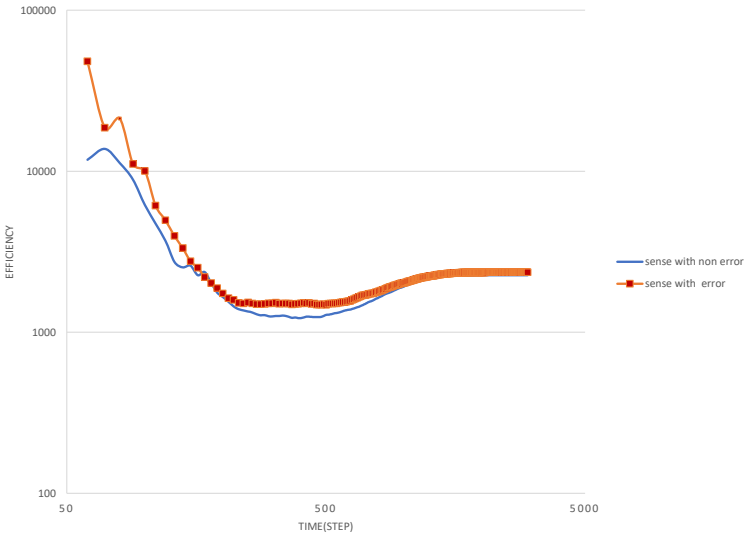

Fig. 12 Comparison of the effect of error on the performance of the proposed algorithm

number of available food and carrier food tends to zero, and the collected food approaches the final number.

4.6 Scenario 5: Investigating the Effect of Error Noise

This experiment is designed to assess error on agents' perception to evaluate the robustness of the proposed model. The error of agent perception in detecting the conducting acoustic signal has been increased by 50We then what effect this rate of error has had on the general behaviour of the model is examined. As shown in figure 12, this error at the beginning of the foraging process increased the initial irregularity in the search process. But after, the system has been adapted to this error, the final goal has been achieved with only more efficiency.

5 Conclusion

Using acoustic signals in real-world applications is more suitable than synthetic pheromone and light waves and is more practical and cost-effective for communicating between robots. Inspired by the social calls of bats, we have

proposed a way for communication and coordination between agents. In this method, instead of calling echolocation, the agents emit sound waves when they are near the food or nest site, and the rest of the agents around find the target position by eavesdropping and orienting towards it. In this algorithm, which is based on the self-organizing system, the replication of social calls in a communication network favors the positive amplification of attraction signal and the physical specificity of an acoustic signal, which reduces the intensity of waves according to the distance from the sound source. To create a potential field of sound waves that can be approached to the target by tracking the increasing trials of sound intensity.

In this study, a new solution to the main challenge in the foraging field, the optimal allocation of tasks, is presented. The agents have been reaching the goal, and helping to attract the participation of other agents by emitting sound waves, and their persistence is determined by perceiving and processing the number of new employment agents, the amount of food available, and the time threshold probabilistic model. This mechanism creates a balance between extraction and exploration and increases system efficiency.

This study assumes that the agents do not have orientation and positioning tools, have limited memory and processors, and the range of sound waves propagated covers a limited area. However, these agents achieve the necessary coordination to emerge a general behaviour by cooperating, attracting collective participation and changing the roles performed without a central controller.

To evaluate the proposed model, we designed different scenarios, and the results show that the agents' behaviour after a third of the total search time leads to general convergent behaviour. We simulate unknown environments with various obstacle densities, and have shown that the effectiveness of this algorithm is stable in these environments. We have also examined the effect of increasing the number of agents on the number of foods saved per unit time and showed that the number of agents more than a certain level does not affect the energy carapace. We have also examined the effect of error perception of the signals received by the agents and showed that in the event of an error in open environmental perception, the system could update its general behaviour and achieve the desired goal.

6 Declarations

6.1 Ethics approval and consent to participate

The authors approve their participation in this manuscript.

6.2 Consent for publication

the authors consent for publication in Swarm Intelligence.

6.3 Availability of data and material

Data available on request from the corresponding author.

6.4 Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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6.6 Authors' contributions

The authors have equal contribution.

6.7 Acknowledgements

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