Energy Consumption Minimized Task Allocation with Correlated Data for Symbiotic Robotic Swarm

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***Abstract*—In this paper, computational task allocation schemes with correlated data are investigated to minimize the energy consumption for symbiotic robot swarm. In such swarm, task needs to be computed cooperatively with the data from multiple robots. Therefore, data need to be transmitted to one selected robot. However, the correlated data among robots can increase the energy consumption of transmission and computation due to the reduandunt. To solve this problem, a model is proposed to investigate the data correlation versus distance among the robots. Based on this model, three task allocation strategies are further proposed. Energy consumption of the robot swarm is reduced through selected robot to transmit data either based on channel gain or data correlation. MATLAB based simulation results show that the proposed task allocation strategies can significantly reduce the energy consumption of symbiotic robotic swarm compared to state-of-the-art.**

***Index Terms*—Task allocation, symbiotic robot swarm, data correlation.**

I. Introduction

As technology has advanced, robotics has made great achievements. During this time, many advanced robotic applications have emerged [1]. Robot swarms are one of the most fascinating areas of research, where robots share resources for mutual benefit. Simply structured robot swarms can replace complex, powerful single robots or multi-robot systems and are used to solve a variety of dirty, dangerous and tedious tasks [2], [3]. However, one of the most challenging problems in robotic crowd systems is how to rationally assign one or more tasks to a crowd of robots in order to optimise the overall performance of the system under a set of constraints. This is because robots have extremely limited computational resource and battery power. Moreover, as the task performed by robot swarm becomes more complex and the scenarios more demanding, conventional robot swarm cannot meet the demands.

Recently a new robotic swarm system called a symbiotic swarm has been proposed. Such kind of robot swarm can be used to perform computational task but requiring a certain number of robots to work cooperatively [4]. If the total number of the active robots is less than the required one, the task cannot be performed [5]. In order to maximize the number of tasks can be accomplished, it is important to minimize the energy consumption. Such problem is so called lifetime maximization, and investigated in sensor networks. However, in some cases, data among robots needs to be transmitted to a voted robot for computation purpose, therefore, the correlated data can cause extra energy computation due to the redundancy [6]. Many approaches have been proposed in literature to solve this problem. For example, a group level devices selection approach has been proposed in [7]. Within each group, the robot with the most private message will be selected to transmit the data to the voted devices served as head. By doing this way, the common message can be minimized in device level, but there is still redundant message transmitted.

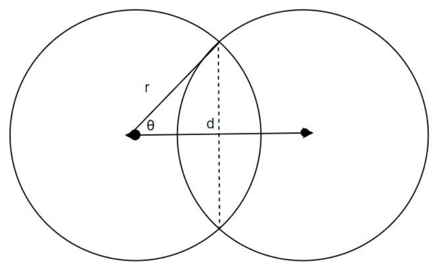

Fig. 1. Data Correlation Model

In our work, the robot swarm is considered as working closely to each other. This consideration can further increase the amount of common message for each robot as the data collected by each robot is correlated. The energy consumption for computing and transmitting such common message will be considerable as well. Therefore, to further remove the common message from the selected robot to transmit is our target. In this paper, a robot will be voted in the robot swarm to serve as the head to compute the data of the task. Since the head cannot compute the task with its own data, another robot within the swarm will be selected to transmit the data to head for computation purpose. A new model is proposed to measure the data correlation among robots based on locations. Further more, robots selection approaches are also proposed based on the proposed correlation models to minimize the energy consumption for the symbolic robot swarm.

II. System Model Problem and Formulation

A. Data Correlation Model

In this subsection, a location based data correlation model is proposed as following. The correlation among the data collected from the different robots and the information collected by the head differs because of the different distances between the individual robots and the head, as shown in Fig. 1. Since

each robot in the robot swarm is considered as identical, the radius of the data collected by the robot is r. The distance between the two robots is d.
According to the cosine theorem it follows that:

$$\cos\theta = \frac{r^2 + d^2 - r^2}{2rd} \tag{1}$$

Therefore θ can be expressed as:

$$\theta = \arccos\left(\frac{d}{2r}\right) \tag{2}$$

Area of the correlated part of the data collected by the two robots, that is the area of the part of the two circles that overlap, S_{c} can be expressed as:

$$S_{\mathrm{c}} = 2\cos^{-1}\left(\frac{d}{2r}\right) r^2 - d\sqrt{r^2 - \frac{d^2}{4}} \tag{3}$$

The ratio α of the correlated parts of the data collected by two robots to the total amount of data collected by one robot can be expressed as

$$\begin{aligned}\alpha &= \frac{S_{\mathrm{C}}}{S} \\ &= \frac{2\cos^{-1}\left(\frac{d}{r}\right)^2 - d\sqrt{r^2 - \frac{d^2}{4}}}{\pi r^2} \\ &= \frac{2\cos^{-1}\left(\frac{d}{2r}\right)}{\pi} - \frac{d\sqrt{\mathrm{r}^2 - \frac{rd^2}{4}}}{\pi r^2}\end{aligned} \tag{4}$$

Performing a Taylor first-order expansion on the Eq.(4), it can be expressed as

$$\alpha = 1 - \frac{d}{2r}, \alpha \in [0,1], d \in [0,2r] \tag{5}$$

B. Energy Consumption Model

A robot swarm is made up of M robots, denoted by $\mathbb{M} = \{1, 2, 3, ..., m\}$, as shown in Fig. 2. They are randomly distributed over a limited area. Each robot can share location information with other robots. In addition, the channels between each robot are orthogonal. A head is selected from the robot population. First, the head broadcasts its data to the other members. Each member then calculates the correlation between the data broadcast by the head and the data it has collected [8]. We assume that each decision to perform a task requires two sets of data to be completed, namely the data from the head itself and the data that is selected for transmission to the robot. The robot can therefore send back to the head data that is not relevant to the head. Finally the head does the data calculation. Since the head selected for each completed decision and the robots selected for transmitting data are independent of each other, the energy consumption of the swarm of robots can be written as follows.

$$E_{\mathrm{sum}} = E_{\mathrm{pro}} + E_{\mathrm{com}} \tag{6}$$

As the robots in the robot swarm system are of the same type, all robots have the same battery capacity. And the energy consumption to perform the calculation is the same for each robot. Therefore, the energy consumed by the robots during their movement and process is not considered in this project. The main objective here is to extend the lifetime of the whole system while satisfying the minimum number of robotic swarms required. The objective function is.

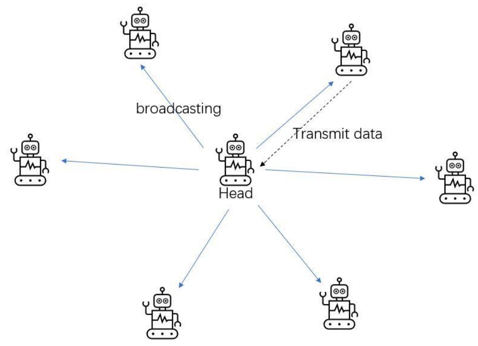

Fig. 2. Illustration of task allocation for a symbiotic robotic swarm system

$$\begin{aligned}E_{\mathrm{sum}} &= \min E_{\mathrm{com}} \\ &= \min\left(E_{m_{\mathrm{H}}} + E_{\mathrm{m}}\right)\end{aligned} \tag{7}$$

subject to:

$$m \neq m_{\mathrm{H}}$$

$$M \geqslant \bar{m}$$

$E_{m_{\mathrm{H}}}$ is the energy consumption of the head and E_{m} is the energy consumption of the robot selected to return the data, M is the number of robots alive, $\overline{m}$ is the minimum number of robots alive.

Since the head needs to broadcast its data to the other members, the header only consumes broadcast energy. Thus the energy consumed by the header can be expressed as.

$$E_{m_{\mathrm{H}}} = E_{\mathrm{bro}} \tag{8}$$

On the other hand, the head selects a robot to transmit the data to the head. The energy consumption of the robot can be expressed as.

$$E_{\mathrm{m}} = E_{\mathrm{tra}} \tag{9}$$

In this model, the transmission can be successful only when $\frac{D}{t} \leqslant C$. where C is the channel capacity, E is the transmission energy, $|h_{\mathrm{H,r}_m}|$ is the channel gain when the head broadcasts to the mth robot, and σ^2 is the noise power. D is the fixed data size of the transmitted data. t is the time required to transfer the data. According to the hannon's formula, the energy consumed by head broadcast E_{bro} is determined by Eq.(10)

$$E_{\mathrm{bro}} = \frac{\left(2^{\frac{D}{t}} - 1\right)\sigma^2}{|h_{\mathrm{H,r}_m}|} \tag{10}$$

Similarly, the energy consumed by the robot to transmit data E_{tra} is determined by Eq.(11)

$$E_{\rm tra} = \frac{\left(2^{\frac{(1-\alpha)}{t}} - 1\right)\sigma^2}{|h_{{\rm b}_n,{\rm H}}|} \tag{11}$$

The data correlation is represented by α. α is a number between 0 and 1. $n \in (1, 2, 3 \cdots N)$. N represents the number of robots for which the data is sufficient. $|h_{{\rm b}_n,{\rm H}}|$ is the channel gain when the nth robot transmits data to the head.

In summary, the energy consumed by the system allocated for a computing task can be expressed as

$$E_{\rm sum} = \min\left[\frac{\left(2^{\frac{D}{t}} - 1\right)\sigma^2}{|h_{{\rm H},{\rm r}_m}|} + \frac{\left(2^{\frac{(1-\alpha)}{t}} - 1\right)\sigma^2}{|h_{{\rm r}_m,{\rm H}}|}\right] \tag{12}$$

Where $|h_{{\rm r}_m,{\rm H}}|$ is the channel gain when the mth robot transmits data to the head.
Taking Eq. (4) into Eq. (12), we get Eq. (13)

$$E_{\rm sum} = \min\left[\frac{\left(2^{\frac{D}{tB}} - 1\right)\sigma^2}{|h_{{\rm H},{\rm r}_m}|} + \frac{\left(2^{\frac{d}{2rtB}} - 1\right)\sigma^2}{|h_{{\rm b}_n,{\rm H}}|}\right] \tag{13}$$

In Eq.(13), the partial derivative of d is given

$$\frac{\partial E_{\rm sum}}{\partial d} = \frac{\left(\frac{2^{\frac{d}{2rt}} ln2}{2rt} - 1\right)\sigma^2}{|h_{{\rm b}_n,{\rm H}}|} \tag{14}$$

With Eq.(14), It can be found that $E_{\rm sum}$ is similarly monotonically increasing on $(0, 2r)$. Thus, the smaller the distance between the robot and the head, the less transmission energy is consumed by the whole symbiotic robot swarm system.

III. PROPOSED TASK OFFLOADING ALGORITHM

A. Head Selection Method

The way the head is selected in a symbiotic robot population is based on the minimum sum Euclidean distance to the other robots. This is to save the energy consumption of the head broadcasting to other members of the robot swarm. The specific steps of this algorithm are as follows:

- Each robot can transmit its two-dimensional coordinates to other robots via GPS or other means. Each robot calculates its Euclidean distance to other robots based on the collected coordinates.
- Each robot calculates the sum of its Euclidean distances to other robots.
- The robot with the minimum sum of Euclidean distances is selected as the leader.

$$d_i = \sum_{j=1, i\neq j}^{J} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{15}$$

$$i_{\rm min} = arg\, min_i\ d_i \quad i = 1, 2, \ldots, I. \tag{16}$$

- (x_i, y_i) is the coordinates of the selected robot, (x_j, y_j) are the coordinates of robots other than the selected robot. d_i is the sum of the Euclidean distances from the selected robot to the other robots. $i_{\rm min}$ is the index of the minimum value of the sum of the Euclidean distances for the selected robot. The pseudo-code of the algorithm is as follows.

B. Broadcost Methods

- To ensure that all robots in the swarm can receive the information broadcast by the head, the head chooses the channel with the worst channel quality among its channels for other members to broadcast.

$$H_{\rm min} = arg\, min_m\, |h_{{\rm H},{\rm r}_m}|, \quad m = 1, 2, \ldots, M-1. \tag{17}$$

Bringing $H_{\rm min}$ into Eq. (10) gives

$$E_{\rm bro} = \frac{\left(2^{\frac{D}{t}} - 1\right)\sigma^2}{H_{\rm min}} \tag{18}$$

- Since non-line-of-sight (NLoS) and line-of-sight (LoS) are considered. To save the head's energy, the head chooses only the worst channel quality for broadcasting among the bots of the Rician fading channel.

$$H^*{}_{\rm min} = arg\, min_{m^*} |h_{{\rm H},{\rm r}_{m^*}}|\ , \quad m^* = 1, 2, \ldots, M^*. \tag{19}$$

- To further conserve the head's energy, the head chooses the robot with the best channel quality to broadcast among those whose data is sufficient.

$$H_{\rm max} = arg\, max_n |h_{{\rm H},{\rm r}_n}|\ , \quad n = 1, 2, \ldots, N. \tag{20}$$

C. Transmission Methods

- Transmission method I: After members receive the broadcast data, they calculate the correlation between their data and the broadcast data, and then the head selects the robot with the strongest data correlation among the robots that match the hypothesis to transmit the data.

$$\alpha_{\rm max} = arg\, max_n\ \alpha_n \quad n = 1, 2, \ldots, N. \tag{21}$$

where α_n represents the data correlation of the nth robot. Bringing $\alpha_{\rm max}$ into Eq.11 gives

$$E_{\rm tra} = \frac{\left(2^{\frac{(1-\alpha_{\rm max})D}{tB}} - 1\right)\sigma^2}{|h_{{\rm b}_n,{\rm H}}|} \tag{22}$$

- Transmission method II: After calculating the correlation, the robot with the best channel quality (instantaneous) to the head is allowed to transmit the data among the robots that match the hypothesis.

$$H^{'} = arg\, max_n |h_{{\rm b}_n,{\rm H}}|\ , \quad n = 1, 2, \ldots, N. \tag{23}$$

Bringing $H^{'}$ into Eq.11 gives

$$E_{\rm tra} = \frac{\left(2^{\frac{(1-\alpha)}{t}} - 1\right)\sigma^2}{H'} \tag{24}$$

- Transmission method III: Since the robots know their channel quality and data correlation, the ratio of data correlation is ranked from smallest to largest and the robot with the lowest energy consumption is selected for transmission.

$$\alpha^* = arg\,max_n \underset{s.t\ E_{\min}^{\text{tra}}}{\alpha_n} \quad n = 1, 2, \ldots, N. \qquad (25)$$

IV. Simulation Results

This section presents and analyses the results of simulations of a symbiotic robot swarm under different ways of broadcasting information from the head for computation task allocation. The parameter settings in the simulations are shown in the table below.

Monte Carlo trial	$5 * 10^3$
The given target BER	1×10^{-4}
The maximum number of the robots	10
The minimum number of the robots	5
The battery capacity of the robot	16dB
Channel	Rayleigh and Rician channel
Modulation	4QAM

A. Broadcast for the robot with the worst channel quality of all robots

1) Different head voted methods: The results of the different data transfer methods compared to SoTA are shown in the following figures.

Where the head is voted by maximum residual energy is SoTA1 [9].

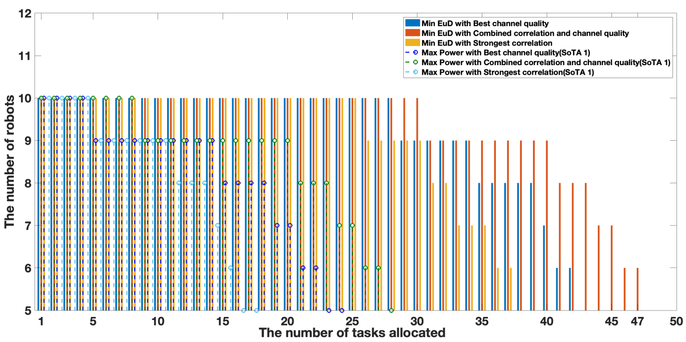

Fig. 3. Comparison of proposed head selection method with SoTA1, based on best channel quality

As shown in Fig. 3, the proposed head selection method works better than SoTA1 for each of how the robot transmits data. This is because of the Euclidean distance-based captain selection approach. When choosing among compliant robots, the robot selected to transmit data is closer to the captain. And the data relevance of the robots is proportional to the distance between the robots, so the closer the robot to the captain the greater the data relevance. The smaller the amount of data that needs to be transmitted. However, in SoTA1 the robot may select to be far away from the head, so the data relevance of the robot is smaller in comparison. Furthermore, the energy consumption of the robot to transmit data increases when the distance between the robot and the head increases under the influence of a wide range of attenuation.

2) Different data transmission methods: The results of the different data transfer methods compared to SoTA2 are shown in the following figures.

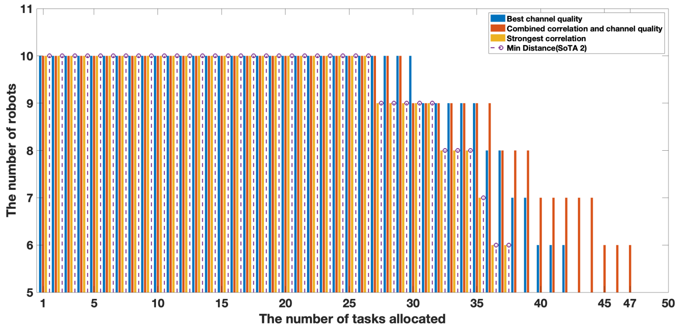

Fig. 4. Propose transmission method versus SoTA2

Where the robot closest to the head transmits the data as SoTA 2 [10].

From Fig. 4, we can see that selecting the robot with the greatest data correlation to transmit the data has the same effect as SoTA 2. This is because the correlation of the data is determined by the distance between the robots. Of the robots available, the robot closest to head has the greatest data correlation. Therefore the same robot is selected for both approaches.

B. Broadcast for the robot with the worst channel quality of the Rician channel robots

1) Different head voted methods: Where the selection of the head by residual energy is SoTA1.

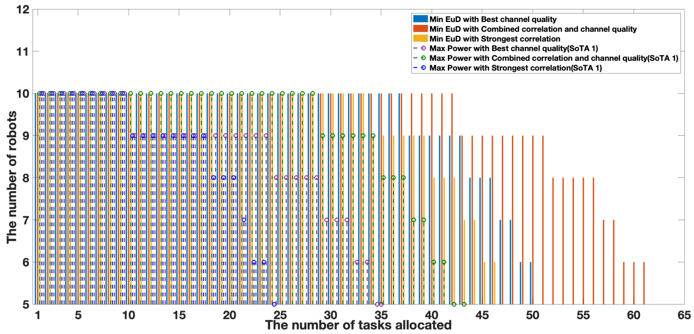

Fig. 5. Propose transmission method versus SoTA

As shown in Fig. 5. They all performance better than Fig. 3. This is because the way header broadcasts changes to broadcast for the robot in the Rician channel. Then the head can also only choose among robots whose channel is the Rice channel when selecting robots to transmit data. This reduces the energy consumption of the robot when transmitting data. Furthermore, although the head broadcasts in different ways, the proposed head selection method works better than SoTA2 for each of how the robot transmits data.

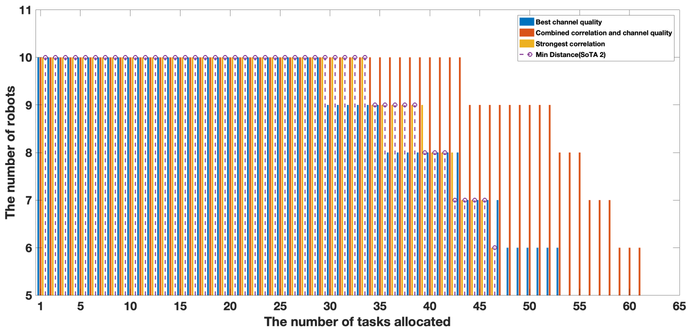

Fig. 6. Propose transmission method versus SoTA2

2) Different data transmission methods: From Fig. 6, we can similarly see that selecting the robot with the greatest data relevance to transmit data has the same effect as SoTA2. In addition, the robot population performs an increased number of tasks compared to Fig. 4. This is because the head only broadcasts to the robots on the Rician channel. This saves the energy consumed by the head.

C. Broadcast for the robot with the best channel quality of all robots

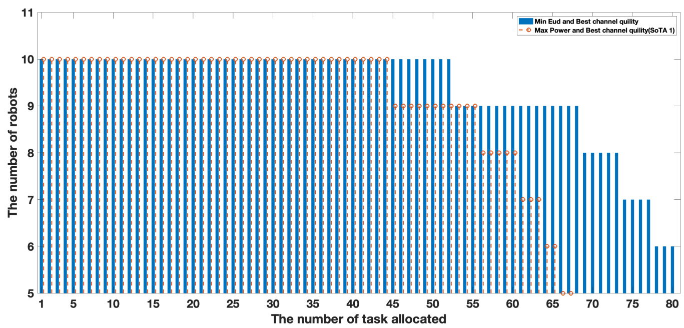

Fig. 7. Propose head selection method versus SoTA1

This is an extremely special case. The head broadcasts the data only to the robot with the best channel quality and chooses this robot to transmit the data. This saves the head a lot of energy. From Fig. 7, We can see that selecting the head based on the Euclidean distance is better than SoTA1 (selecting the captain based on the maximum remaining energy). This is because SoTA1 does not take large-scale decay into account. The distance between the robot and the head can be very large, so causing an increase in communication energy consumption.

V. Conclusions

The system starts by calculating the average of the sum of the Euclidean distances from the robot to the other robots, selecting the one with the smallest average as the head, which then broadcasts the data collected by itself, and finally selecting the robot to return the data by the proposed algorithm. Simulations have been carried out for the proposed broadcast method and algorithm. The simulation results show that the method can perform more tasks than the traditional task allocation method, which means that the running time of the robot will be improved. For the selection of the head, a selection method based on Euclidean distance is proposed, where the robot with the smallest sum of average Euclidean distances is the head. This can reduce energy consumption when the head broadcasts information. Secondly, for the task allocation strategy, it is suggested that the robot with the least data correlation be allowed to transmit and the robot with the best channel quality be allowed to transmit, respectively. To improve the disadvantages of these two data transmission methods, a third approach is proposed that combines both methods. The robot with the lowest transmission energy is chosen to transmit the data. In all three approaches, the correlation of the data is reduced by the channel gain of the robot. The energy consumption of the robot in transmitting the data can be reduced. As a result, the energy consumption of the entire robot population during task allocation can be reduced, extending the usage time of the system. Using the simulation results, we can conclude that the proposed task allocation strategy can effectively reduce the transmission energy consumption of the robot. It has significant advantages compared to the SoTA method.

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