Efficient collective search by BRT algorithm using fast rising threshold agent

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ABSTRACT

The BRT algorithm is a method for the best-of-n problem that allows a group of distributed robots to find out the most appropriate collective option among many alternatives. Computer experiments show that the time required for finding out the best option is proportional to the number of options. In this paper, we aim to shorten this search time by introducing a few agents whose threshold increases faster than the normal one to achieve higher scalability of the BRT algorithm. The results show that the search time is reduced, and the variance is improved, especially under challenging problems where robots are required to make decisions out of a large number of options.

Keywords: Best-of-n problem, BRT algorithm, Swarm robotics, Collective decision-making.

1. INTRODUCTION

In recent years, as robots and software agents have become popular, the research on the behavior of swarm robotics, called the Collective Decision-making phenomenon, has been actively studied. Optimality of the system achieved by individual decision-making is essential for engineering applications and understanding our society more deeply. That is why this phenomenon is studied in many different disciplines, including Game theory, multi-agent systems, and distributed artificial systems.

The best-of-n (BSTn) problem is an important research area in Collective Decision-making that focuses on finding out the question of how a robot swarm can discover the best choice from a set of many options without a leader [1]. In several robotic scenarios, the terminology “option” may be a prey in the prey-hunting scenario [2], a bridge in the double-bridge scenario [3, 4], or a nest-side in the binary aggregation scenario [5, 6]. While the BSTn problem has been kept attention for almost 20 years, the methods used in the above scenarios are just efficient for simple environments where robots in swarm face a binary-option problem.

Research focusing on the multi-option domain ($n > 2$) is getting more attention in recent years. This research opens up the hope of blurring the line between robot swarm and natural swarms such as schools, the flock of birds, or foraging ants can make an optimal collective decision among many options ($n >> 2$) [7, 8]. Reina et al. proposed a method based on the nest-site selection of honeybees [9, 10]. This method allows robots to decide on the optimal option among multiple options. The correct decision is taken in at least 75% when $n \leq 7$. In 2017, Hasegawa et al. applied a sensory discrimination mechanism using yes/no agents with differential thresholds [11]. The proportion of correct choices is more than 80%. However, in these methods, the number of options that robots can deal with is small with not high scalability.

To tackle this problem, we have proposed Bias and Raising Threshold (BRT) algorithm that enables robot swarms to solve more complex BSTn problems in which robots have to face a large number of options [12]. We introduced a social model based on majority rule to a trial and error process. Each robot considers to changes its option by monitoring the number of supporters of its recurrent option. Robots keep voting until all members agree with the best option. Therefore, the BRT algorithm is potentially effective in maintaining the homeostasis of groups and finding out the best option among many options with very high accuracy. However, the experimental results showed that it sometimes takes a large amount of time to find the best option. This is inefficient when the search time is limited or a short time is desirable.

In this paper, we proposed an extension of the BRT algorithm for more efficient searching by introducing a derivation agent with a different rate of the rising threshold. The results show that the search time is reduced and variation is improved, especially under challenging problems where robots are required to make decisions out of a large number of options.

The remainder of this paper is organized as follows. In Section 2, we describe the proposed method. In Section 3, we validate the effectiveness of the proposed method by using computer experiments. Finally, in Section 4, we present the conclusions.

2. PROPOSED METHOD

2.1. Social Model [13]

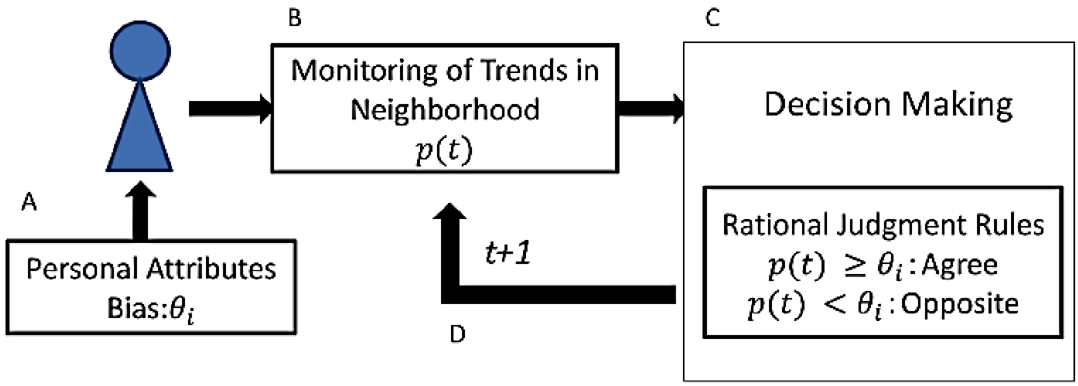


Figure 1. *Role of social skin in individual decision-making [13].*

BRT algorithm is inspired by a social model in which the choice of all individuals in a group will converge rapidly to **Agree** or **Opposite** [13]. Thus, we explain in detail this social model.

Assume that there is a group of people who have to choose to agree or disagree with an opinion. For example, people have to agree to the new business plan at their company meeting, or students in a class have to vote to go to the zoo or the museum at the weekend. As shown in figure 1, Iwanaga et al. stated that individual decision-making depends not only on personal philosophy and personal preferences but also on the atmosphere of the whole group. In other words, an agent determines its chosen based on its attributes, here we call bias value θ, and by looking at the rate of agreed members to the option ($p(t)$). More specifically, as shown in equation (1), an agent will agree if the rate of agents who agree with the opinion ($p(t)$) is higher than its bias value (θ_i).

$$\begin{cases} p(t) \geq \theta_i & Agree \\ p(t) < \theta_i & Opposite \end{cases} \quad (1)$$

Iwanaga et al. clarified that if the cumulative distribution of bias value θ forms an S-shaped curve, as shown on the right side of figure 2, all members smoothly move their opinions to agree or disagree ultimately.

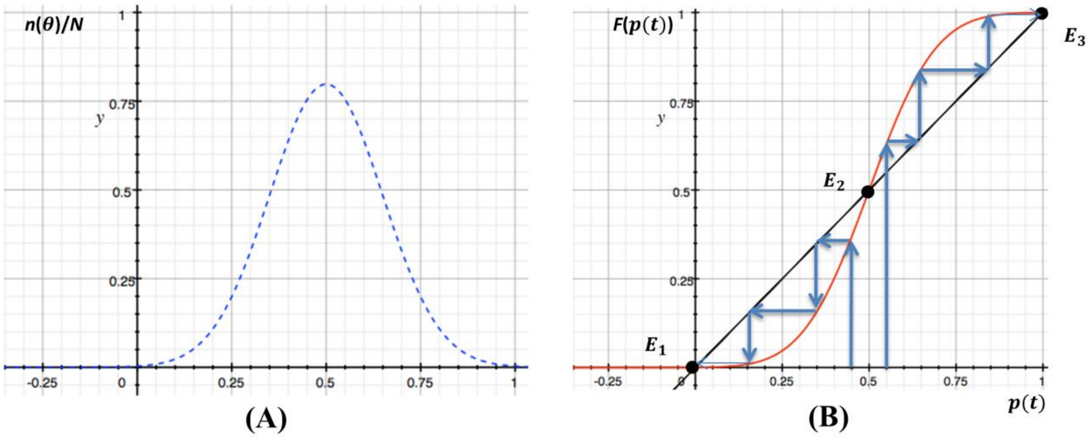


Figure 2. *An example of bias distribution (A) and its cumulative distribution function. (E1 and E3 are stable points, E2 is an unstable point) [13].*

If the distribution shape of the bias value θ is bell-shaped (figure 2A), the number of iterations until convergence does not depend on the number of individuals. Thus, it is possible to expect that the convergence will be achieved promptly even with a large number of individuals. However, this model was not expanded to the BSTn problem, and failure recovery dynamics were not discussed.

2.2. BRT Algorithm [12]

Here, we describe the BRT algorithm, a social model for a complex BSTn problem ($n \geq 2$). The number of options is written as M instead of n in following to avoid confusion.

We assume that there are N robots (agents) $P_1, \ldots, P_i, \ldots, P_N$ $(1 \leq i \leq N)$ in the swarm. $A = \{a_1, \ldots, a_j, \ldots, a_M\}$ is a set of options that robots have to make decision with. M is the number of options and $M \geq 2$ $(1 \leq j \leq M)$. (a_j) represents the number of robots choosing option a_j. $A_i(t) \in A$ is the current option that robot P_i at chosing at time t and a_{goal} is the best option that the swarm have to find out ($a_{goal} \in A$). Robots do not know whether their current option is the best one until they archive agreenment state where all robots choice a same option $((A_i(t) = N))$. The robot P_i has the bias θ_i represent his personal preference $(0 \leq \theta_i \leq 1)$, which is generated from a Gaussian distribution [12].

The robot P_i decides his next time option $A_i(t+1)$ at time t as follows. If

$$\frac{n(A_i(t))}{N} \geq \theta_i + \tau \cdot c(t) \cdot (t - t_{i,last}) \quad (2)$$

is satisfied, he will keep choising the current option, i.e., $A_i(t+1) = A_i(t)$. Otherwise, he will stochastically choice another option, i.e, $A_i(t+1) \in A \setminus A_i(t)$.

τ is a constant representing the *impatience* of robots. If τ is small, robots tend to maintain the current option for a long time, whereas if τ is large, robots will tend to move to another option faster.

In addition, $t_{i,last}$ is the time when the robot P_i last changed its option, and $\left(t - t_{i,last}\right)$ is the time span that the same option continues to be chosen.

$$t_{i,last}(t+1) = \begin{cases} t+1 & A_i(t+1) \neq A_i(t) \\ t_{i,last}(t) & otherwise \end{cases} \tag{3}$$

$c(t)$ is a function that is equal to 1 or 0 depending on the follows:

$$c(t) = \begin{cases} 0 & \forall i, A_i(t) \equiv a_{goal} \\ 1 & otherwise \end{cases} \tag{4}$$

Thus, if the robot P_i see that the rate of robots who select the same option as theirs is lower than $\theta_i + \tau \cdot c(t) \cdot (t - t_{i,last})$, he will choice a new option from other $M-1$ candidate options. The second term on the right side of (4) will increase its value by the time elapsed.

2.3. Proposed Method

In natural swarms such as ant colonies, there are always 80% hard-working ants and 20% lazy ants [14]. This phenomenon makes they can always maintain the optimal state of food. The phenomenon has been modeled and is well known as the fixed response thresholds model [15]. Individuals with different thresholds respond differently to the stimuli. Thus, by introducing a few robots with different thresholds, we expect the swarm to achieve the optimal state more efficiently.

As the analysis and results in [16], the search time required to find out the best option depends on the number of options M and the *impatience* of robots τ. Here, we focus on shortening the search time by using a few robots that have higher *impatience*. In other words, we introduce a few fast raising threshold (FRT) robots in into the swarm of BRT robots.

Here, we consider a same problem with the problem defined in section 2.2. p_{FRT} is ratio of FRT robots in the swarm. The FRT robots have *impatience* τ_{FRT}, and the BRT robots have *impatience* τ_{BRT} ($\tau_{FRT} > \tau_{BRT}$). Thus, the FRT and BRT robots are based on the following decision-making rules, respectively:

$$\frac{n(A_i(t))}{N} \geq \theta_i + \tau_{FRT} \cdot c(t) \cdot (t - t_{i,last}) \tag{5}$$

and

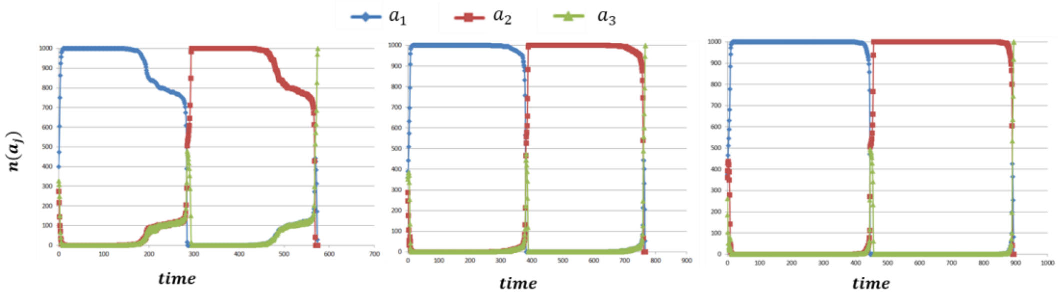
$$\frac{n(A_i(t))}{N} \geq \theta_i + \tau_{BRT} \cdot c(t) \cdot (t - t_{i,last}) \tag{6}$$

Where P_i could be FRT robot or BRT robot.

3. RESULTS AND DISCUSTION

3.1. Dynamics of the Decision-making Process

Here, by the computer simulations, we show an example of the dynamics of the best option searching process. The parameters are set as follows: $N = 1000, M = 3,\ \tau_{BRT} = 0.003$, $a_{\text{goal}} \equiv a_3$. At the initial, all robots randomly choice their option. Figure 3 shows the transition of number robots selecting each option. The horizontal axis represents time and the vertical axis represents the number of robots selecting each option. As can be seen, in all cases, the swarm could reach the agreement state and find out the best option a_3. In addition, we can see that the higher τ_{FRT} is, the shorter time required for an agreement (around 300, 400, and 450 time step for $\tau_{FRT} = 3, 1.5, 1.05\tau_{BRT}$, respectively). Thus, it's expected that the proposed method enables to improve the searching time. Moreover, in the case shown in figure 3a, the agreement state on wrong option (a_3) was broken early at around 150 time step. This caused the swarm to restart early the confusion voting and the other agreement was achieved sooner. These results show a positive potential of the proposed method to improve the performance of swarm decision-making.



(a) $p_{FRT} = 0.2$, $\tau_{FRT} = 3\tau_{BRT}$ (b) $p_{FRT} = 0.05$, $\tau_{FRT} = 1.5\tau_{BRT}$ (c) $p_{FRT} = 0.05$, $\tau_{FRT} = 1.05\tau_{BRT}$

Figure 3. *The transition of number robots selecting each option.*

3.2. Improvement of Searching Time

Here, we focus on clarifying the improvement of the search time in the proposed method. We set that $N = 1000, M = 10,\ \tau_{BRT} = 0.003,\ a_{\text{goal}}\ \equiv a_{10}$ and 30000 limited time steps. We changed the rate of FRT robots for each following case: $\tau_{FRT} = 3, 1.5\ and\ 1.05\tau_{BRT}$ and run 10000 trials. The result is shown in figure 4. The horizontal axis represents the rate of FRT robots, the vertical axis represents the average of searching time in 10000 runs, and the marked lines show the average searching time of the 3 cases. The result shows that the more FRT robots we used, the more search time we could shorten even while the rate of FRT is small such as $p_{FRT} = 0.05$ or $p_{FRT} = 0.1$. In addition, higher τ_{FRT} allows more efficient searching.

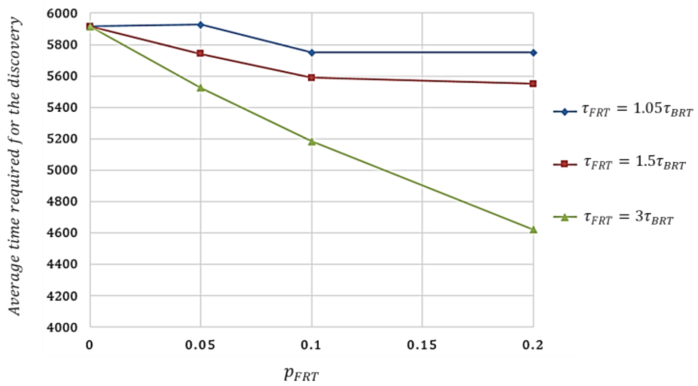


Figure 4. *Average time required to find out the best option in 10000 runs.*

From the above, compare with the original BRT algorithm ($p_{FRT} = 0$), introducing FRT robots could shorten the search time.

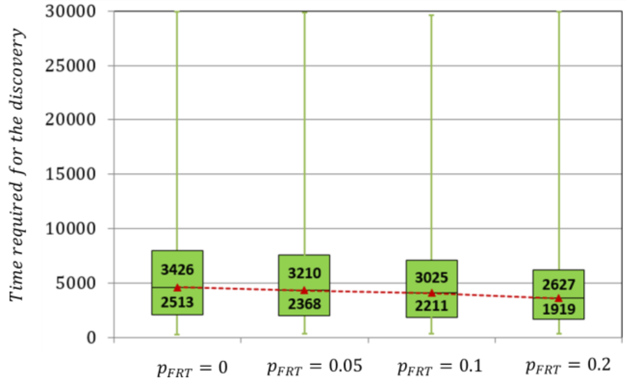


***Figure 5.** Relationship between $\boldsymbol{p_{FRT}}$ and searching time in the case $\boldsymbol{\tau_{FRT} = 3\tau_{BRT}}$.*

Figure 5 is a box-and-whisker plot that shows the relationship between p_{FRT} and searching time in the case $\tau_{FRT} = 3\,\tau_{BRT}$. Triangle marks represent the average search time. We can see that the search time is almost inversely proportional to p_{FRT}. Furthermore, when we increase p_{FRT}, as the size of the box gets smaller, the dispersion of searching time decreases, and the decision-making process becomes more robustness.

Finally, the experimental results show that the efficiency and the robustness of the decision-making can be achive by introducing a few fast raising threshold robots.

4. CONCLUSION

While the BRT algorithm allows swarms to deal with a large number of options, the long time required for finding out the best option is still a disadvantage. In this paper, to improve efficiency in the decision-making process, we proposed a method by introducing a few agents whose threshold increases faster than the normal one. The results show that the search time is reduced, and its variance is improved, especially under challenging problems where robots are required to make decisions out of a large number of options.

REFERENCES

[1]. G. Valentini, E. Ferrante and M. Dorigo, *“The Best-of-n Problem in Robot Swarms: Formalization, State of the Art, and Novel Perspectives”,* Frontiers in Robotics and AI, **Vol. 9**, no. 9, pp. 1-18, 2017.

[2]. J. Wessnitzer and C. Melhuish, *“Collective Decision-Making and Behaviour Transitions in Distributed Ad Hoc Wireless Networks of Mobile Robots: Target-Hunting”,* in Advances in Artificial Life. ECAL 2003, Lecture Notes in Computer Science (W. Banzhaf, J. Ziegler, T. Christaller, P. Dittrich, and J. T. Kim, eds.), **Vol. 2801**, pp. 893–902, 2003.

[3]. S. Garnier, F. Tache, M. Combe, A. Grimal, and G. Theraulaz, *“Alice in pheromone land: an experimental setup for the study of ant-like robots*”, Proceeding of 2007 IEEE Swarm Intelligence Symposium, pp. 37-44, 2007.

[4]. A. Scheidler, A. Brutschy, E. Ferrante, and M. Dorigo, “*The k- Unanimity Rule for Self-Organized Decision Making in Swarms of Robots*”, IEEE Transactions on Cybernetics, **Vol. 46**, no. 4, pp. 1175-1188, 2016.

[5]. S. Garnier, J. Gautrais, M. Asadpour, C. Jost, and G. Theraulaz, “*Selforganized aggregation*

triggers collective decision making in a group of cockroach- like robots," Adapt. Behav, **Vol. 17**, pp. 109–133, 2009.

[6]. H. Hamann, T. Schmickl, H. Wörn, and K. Crailsheim, "*Analysis of emergent symmetry breaking in collective decision making*", Neural Comput. Appl, vol. 21, pp. 207–218, 2012.

[7]. A. Okubo, "*Dynamical aspects of animal grouping: swarms, schools, flocks, and herds*", Adv. Biophys. **Vol. 22**, pp. 1–94, 1986.

[8]. D. J. T. Sumpter, *"Collective Animal Behavior. Princeton",* NJ: Princeton University Press, 2010.

[9]. A. Reina, G. Valentini, C. Fernandez-Oto, M. Dorigo, V. Trianni, *"A design pattern for decentralised decision-making"*, PloS One 10 (10), 2015.

[10]. A. Reina, J. A. R. Marshall, V. Trianni, T. Bose, *"Model of the best-of-N nest-site selection process in honeybees",* Physical Review E, **Vol. 95,** 2017.

[11]. E. Hasegawa, N. Mizumoto, K. Kobayashi, S. Dobata, J. Yoshimura, S. Watanabe, Y. Murakami, K Matsuura, *"Nature of collective decision-making by simple yes/no decision units"*, Scientific Reports, **Vol. 7**, no. 14436, 2017.

[12]. N. H. Phung, M. Kubo, and H. Sato, "*Agreement algorithm with trial and error method at macro level*", Artificial life and robotics, **Vol. 23**, no. 4, pp. 564–570, 2018.

[13]. S. Iwanaga and A. Namatame, *"The complexity of collective decision",* Nonlinear Dynamics, Psychology and Life Sciences, **Vol**. 6, no. 2, pp. 137–158, 2002.

[14]. D. Charbonneau, C. Poff, H. Nguyen, M. C. Shin, K. Kiestead and A. Dornhaus, *"Who Are the "Lazy" Ants? The Function of Inactivity in Social Insects and a Possible Role of Constraint: Inactive Ants Are Corpulent and May Be Young and/or Selfish",* **Vol. 57,** no. 3, pp. 649-667, 2017

[15]. E. Bonabeau, G. Theraulaz and J. Deneubourg, *"Fixed response thresholds and the regulation of division of labor in insect societies",* Vol. 60, pp. 753-807, 1998.

[16]. N. H. Phung, M. Kubo, and H. Sato, "*Efficient searching by bias and raising threshold algorithm using multiple voting in the best-of-n problem*", Vol. 11, no. 3, pp. 39-45, 2019.

TÓM TẮT

TÌM KIẾM BẦY ĐÀN HIỆU QUẢ BẰNG THUẬT TOÁN BRT SỬ DỤNG AGENT CÓ NGƯỠNG TĂNG NHANH

Thuật toán BRT là một phương pháp cho bài toán best-of-n, nó cho phép một nhóm robot phân tán đưa ra quyết định tập thể và tìm ra phương án thích hợp nhất trong nhiều phương án khác nhau. Kết quả thí nghiệm chỉ ra rằng thời gian cần thiết để tìm ra phương án tốt nhất tỷ lệ thuận với số lượng các phương án trong bài toán. Trong bài báo này, chúng tôi đưa ra phương pháp sử dụng một vài robot có ngưỡng tăng nhanh hơn ngưỡng bình thường để rút ngắn thời gian tìm kiếm và nâng cao khả năng mở rộng cho thuật toán BRT. Kết quả thí nghiệm cho thấy thời gian tìm kiếm không chỉ giảm mà còn cải thiện được độ biến thiên, đặc biệt là trong các bài toán khó khi robot cần đưa ra quyết định giữa một lượng lớn các lựa chọn khác nhau.

Từ khoá: Bài toán best-of-n; Thuật toán BRT; Robot bầy đàn; Ra quyết định tập thể.