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ORIGINAL ARTICLE

Guidance by multiple sheepdogs including abnormalities

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Abstract

In this paper, we propose a method for efficiently guiding a large flock of sheep agents through the cooperation of multiple sheepdog agents even in the presence of anomalies, and verify its performance in computer experiments. In particular, this paper evaluates the proposed method extensively in addition to Tashiro et al., (Guidance by multiple sheepdogs including abnormalities. Swarm2021: The Fifth International Symposium on Swarm Behavior and Bio-Inspired Robotics, pp 1818–1823, 2022), and summarizes the effectiveness of the proposed method on six abnormal sheepdog herding systems based on three different anomalies, while changing the size of the herding systems.The results show that the proposed MSR algorithm (LeBlanc et al., IEEE J Select Areas Commun 31(4):766–781, 2013) can guide a group of sheep agents more efficiently and reliably than an efficient extension (Tashiro et al., Herd guidance by multiple sheepdogs. In: Swarm2021: The 4th International Symposium on Swarm Behavior and Bio-Inspired Robotics, 397–408, 2021; Kubo et al., Artif Life Robot 27(2):416–427, 2022) to multiple sheepdogs of the conventional single sheepdog method (Sueoka et al., Trans Jpn Soc Mech Eng Ser C 79(800):1046–1055), even when abnormal sheepdogs are included.

Keywords Swarm Intelligence · MSR algorithm · Malicious Attack

1 Introduction

In recent years, control problems based on the model of a flock of sheep being driven by a small number of sheepdogs have attracted much attention [1–5]. Sheep are usually larger and numerous, and in a simple power relationship, sheep tend to overwhelm dogs. For this reason, sheepdogs seem to guide sheep herds by taking advantage of their flocking characteristics. If we can apply this behavior of the sheepdog, it could be the basis for solving problems where the control input is much less than the control target, such as recovering spilled oil, preventing the spread of forest fires, controlling riotous crowds, and other problems that are currently a problem in the world.

Now, such a geographical robotic system usually is connected to the Internet in some way, and the system must be able to cope with requirements such as robot failure or hacking by malicious entities. Looking back at our social life, problem-solving in such cases is known, for example, (1) to exclude the entities that cannot cooperate and solve the problem only with the remaining ones (exclusion), or (2) to have them participate in solving the problem only when they can cooperate (cooperation). Currently, the s-dog agent model by Tashiro et al [2, 3] is available as a multiple sheepdog model that can be used, which has a sufficient redundancy for breakdowns but solutions to complicated problems such as this failure on the part of the sheepdog have not been considered.

Then to construct an induction method with multiple sheepdog agents that may fall into anomalies, this paper investigates an MSR algorithm suitable for the sheepdog problem, based on the model of s-dog agent (Fig. 1). The MSR algorithm (Mean Subsequence Reduced algorithms) is

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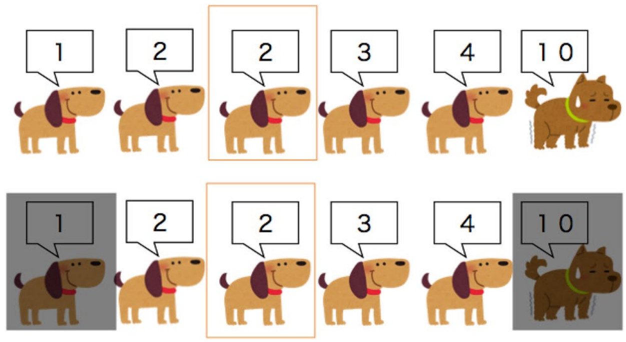

Fig. 1 Mean Subsequence Reduced algorithms (MSR) for sheepdogs

a consensus algorithm proposed by LeBlanc et al. [6]. The MSR algorithm is an anomaly- and attack-resilient consensus algorithm in which each normal agent updates its state at each time, ignoring the information that differs most from its state. This is expected to reduce the influence of abnormal agents by trusting only those agents that are close to their own state.

In this paper, we evaluate the proposed confidence-based MSR algorithm by conducting computer experiments under six kinds of anomalous situations. Firstly we dealt with three types of anomalies related to sheepdogs for understanding basic characteristics: anomalies related to breakdowns (A1w and A1s) and anomalies related to objectives (A2), and matched up three types of sheepdogs (we call them MSR-dog agents) that implement the MSR algorithm against these anomalies in computer experiments. The results showed that the proposed MSR-dog agent groups, which included sheepdogs with abnormalities, could be induced equally or more efficiently than the group of s-dog agent. In particular, it was expected that MSR-dogs tended to perform (cooperation) in A1s and (exclusion) in A2s. Next, we examined the scalability of the proposed method. In [2, 3], improvement in success rate and induction time was reported as the number of dogs increased when no abnormality was included. In this paper, we have investigated the proposed 3 MSR-based counter-strategies for six types of abnormalities in sheepdogs by varying the number of normally working dogs M and the number of abnormal dogs A. The proposed MSR method is found to be generally effective within the scope of this study. The proposed MSR method is generally successful within the scope of this study.

In the next chapter, we explain A-sheep as the target sheep model, and the conventional sheepdog model, s-dog agent by Tashiro et al. [2, 3]. In Sect. 3, the two types of anomalies treated here and the three types of MSR-dog agents of the proposed method, n-dog agent, b-dog agent, and g-dog agent, are proposed. We call them simply n-dog, b-dog, and g-dog in the following. Finally, we describe the computer experiments.

2 Related works

In this section, we explain the s-dog agent [2, 3], which is a guidance model with multiple sheepdogs. We also explain the MSR algorithm [6], which is an approach that enables guidance even if an abnormality occurs in the s-dog agent.

Conventional researches on sheepdog systems have mostly focused on, guided by a small number of sheepdogs, but some studies have addressed guidance by multiple sheepdogs [5, 7, 9–12]. While these studies have shown that many sheepdogs can effectively guide, there has not been enough researches into how several sheepdogs should be deployed in a workspace. On the other hand, Tashiro et.al [2, 3] have shown that a multiple sheepdogs model, called s-dogs, can efficiently induce sheepdogs by introducing repulsion into the conventional model of a single sheepdog. A group of s-dogs is guiding a flock of sheep agents called A-sheep, and the repulsive force generated between the s-dogs creates a formation around the flock of A-sheep, allowing the sheepdogs to be evenly distributed geographically. As a result, the efficient guidance of the flock of sheep agents and the guidance of the flock of sheep agents, which is difficult to achieve by itself, are realized. In this paper, we use this model as a basis to study s-dog agents with anomalies and the MSR algorithm to deal with them.

This paper attempts to clarify the effectiveness of the proposed method experimentally. A mathematical analysis of the method is given, for example, in [14] for the stability of the induction method with a single sheepdog, and in [3] for the stability of induction with multiple sheepdogs. Consensus on the MSR method using graph theory has been done in [6, 15]. However, there is no theoretical analysis of failure among multiple sheepdogs, and we consider this study to be a necessary study in the early stages.

2.1 Sheep agent (A-sheep) [2, 3]

In conventional studies, only one sheepdog is adopted and the sheep agent is defined as accepting only one sheepdog agent. Therefore, a new sheep agent is required for correct assessments that can behave plausibly in a multiple sheepdog environment. Then Tashiro et.al [2, 3] proposed A-sheep based on the conventional sheep method [8]. A-sheep defines the two typical behavior of *flocking sheep* and *escaping from the sheepdog* by concerning the Boid model [13]. In particular, the influence of the sheepdog agent is defined here as the ratio of the total number of sheepdog agents to sheepdog agents in the vicinity of a sheep. In the following, this is called A-Sheep (Fig. 2). Equation 2 defines the acceleration $u_i(k)$ acting on the Sheep agent i at time k,

$$\dot{p}_i(k) = u_i(k) \tag{1}$$

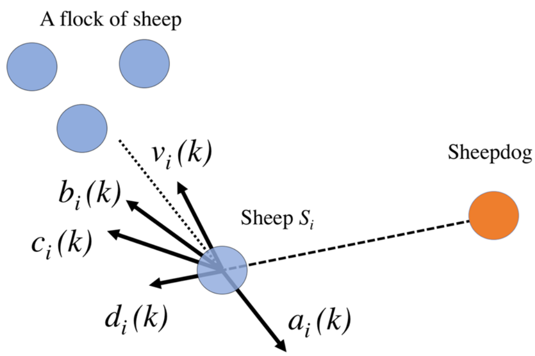

Fig. 2 Sheep agent (A-sheep)

$$u_i(k) = K_{s1}a_i(k) + K_{s2}b_i(k) + K_{s3}c_i(k) + K_{s4}d_i(k) \tag{2}$$

where $a_i(k)$ is the repulsive acceleration acting on the sheep agents, $b_i(k)$ is the alignment term, $c_i(k)$ is the attraction between the sheep agents, $d_i(k)$ is the repulsion to escape from the sheepdog, K_{s1}, K_{s2}, K_{s3}, K_{s4} are the parameters. S_i is the set of sheep in the field of view of sheep i, and D_i is the set of sheep dogs in the field of view of sheep i. N_{S_i} and N_{D_i} are the number of Sheep agents and Sheepdog agents in Sheep agent i's field of vision r_s, respectively.

$$a_i(k) = \frac{1}{N_{S_i}} \sum_{j \in S_i} \frac{x_i(k) - x_j(k)}{||x_i(k) - x_j(k)||^2} \tag{3}$$

$$b_i(k) = \frac{1}{N_{S_i}} \sum_{j \in S_i} \frac{v_j(k-1)}{||v_j(k-1)||} \tag{4}$$

$$c_i(k) = \frac{-1}{N_{S_i}} \sum_{j \in S_i} \frac{x_i(k) - x_j(k)}{||x_i(k) - x_j(k)||} \tag{5}$$

$$d_i(k) = \frac{1}{N_{D_i}} \sum_{j \in D_i} \frac{x_i(k) - X_j(k)}{||x_i(k) - X_j(k)||^3} \tag{6}$$

2.2 Sheepdog agents(s-dog) [2, 3]

In this section, we will discuss s-dog agent, a model that introduces repulsive forces between sheepdogs that perform the farthest individual tracking method proposed by Sueoka et al [8].

$$\dot{p}_i(k) = v_i(k) \tag{7}$$

$$v_i(k) = K_{f1}A_i(k) + K_{f2}B_i(k) + K_{f3}C_i(k) + K_{f4}D_i(k) \tag{8}$$

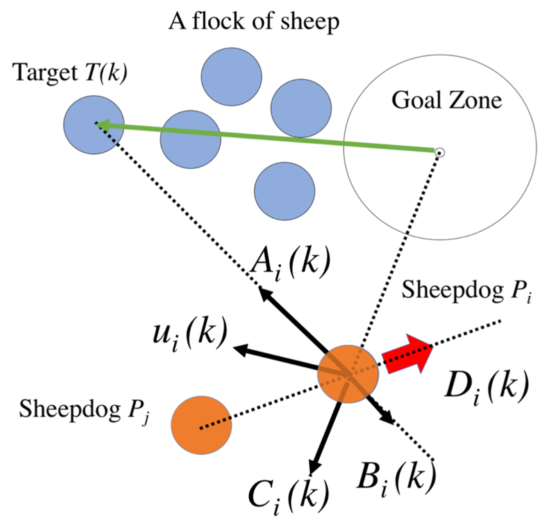

Fig. 3 Sheepdog agent(s-dog)

Equation 8 shows the acceleration $u_i(k)$ acting at time k for the Sheepdog agent i proposed here. Sheepdog Agent i moves by the following four actions. $A_i(k)$ is the action to chase the target Sheep $T(k)$, $B_i(k)$ is the interaction to keep away from the target, $C_i(k)$ is the interaction to keep away from goal G, $D_i(k)$ is the repulsive interaction between sheepdogs proposed here. $T(k)$ is the target sheep, and as in the conventional method [8], the sheepdog operates on a single sheep chosen each step based on a specific criterion. We call the sheep as target sheep. Figure 3 shows these interactions acting on Sheepdog Agent i. N_{P_i} is the number of Sheepdog Agent P_i in the field of view of Sheepdog Agent i.

$$A_i(k) = -\frac{X_i(k) - T(k)}{||X_i(k) - T(k)||} \tag{9}$$

$$B_i(k) = \frac{X_i(k) - T(k)}{||X_i(k) - T(k)||^3} \tag{10}$$

$$C_i(k) = -\frac{X_i(k) - G}{||X_i(k) - G||} \tag{11}$$

$$D_i(k) = \frac{1}{N_{P_i}} \sum_{j \in P_i} \frac{X_i(k) - X_j(k)}{||x_i(k) - X_j(k)||^3} \tag{12}$$

The equations used in this paper are based on the equations proposed in a previous study of sheepdogs [14]. As you pointed out, Eq. 3 expresses the relationship between sheep, and Eq. 10 expresses the relationship between dogs and sheep in a concise manner with different orders, which is a simple and smart way. We also follow this model because the relationship between sheep and dogs is different from the relationship between sheep and dogs, and we expect that by adjusting the order in the future, a wide range of analyses will be possible.

2.3 Circle formation by s-dog agents

In this section, we conceptually explain that the repulsive force K_{f4} causes the s-dog agent to tend to surround the flock of sheep, which can lead the sheep to a fast and efficient way.

The upper row of Fig. 4 depicts guidance by a conventional system of a single sheepdog agent (d). Now the flock is at the left of the goal. There, the sheepdog guides the flock from left to right by moving closer to the sheep farthest from the goal (see a1). The sheepdog in turn shifts the flock to the right, so the sheepdog moves to the right side of the flock (see a3) and pushes the flock from right to left (see a4). By alternating pushing direction to a flock from left and right, the flock is guided to the goal. The lower part of Fig. 4 shows the expected behavior when the proposed sheepdog agents repel each other guide. Suppose we have a pack of three sheepdog agents d1,d2, and d3 now. All sheepdog agents should move to the leftmost sheep (see b1). However, due to mutual repulsion (the yellow marks), d2 and d3 cannot move, and only d1 can move in the direction of the sheep (see b2). Similarly, if the flock shifts to the right, only the d3 on the right can head towards the sheep (see b3). As a result, the three sheepdogs disperse around the flock of sheep (see b4). It suggests that the proposed sheepdog group with the mutual repulsive interaction has the guidance by the circular formation, which has less overshoot.

2.4 Mean subsequence reduced algorithms, MSR [6]

The class called MSR algorithms (Mean Subsequence Reduced algorithms) are consensus algorithms that are resilient to anomalies and attacks. A normal agent updates its state at each update time, ignoring the information that is most different from its state. It does not take into account the past behavior of the agent and does not record it. In the research [15], the following algorithm that extends the work [6], is proposed. The agent i determines input for the control $u_i[k]$ at time k in the following three steps.

1. Each normal agent $i \in U[k]$ sorts the states received from neighboring agents in order of decreasing size.
2. Starting from the smallest value, ignore the largest f in the range not exceeding its own value. Similarly, starting from the largest value, ignore the largest f in the range not less than its own value.

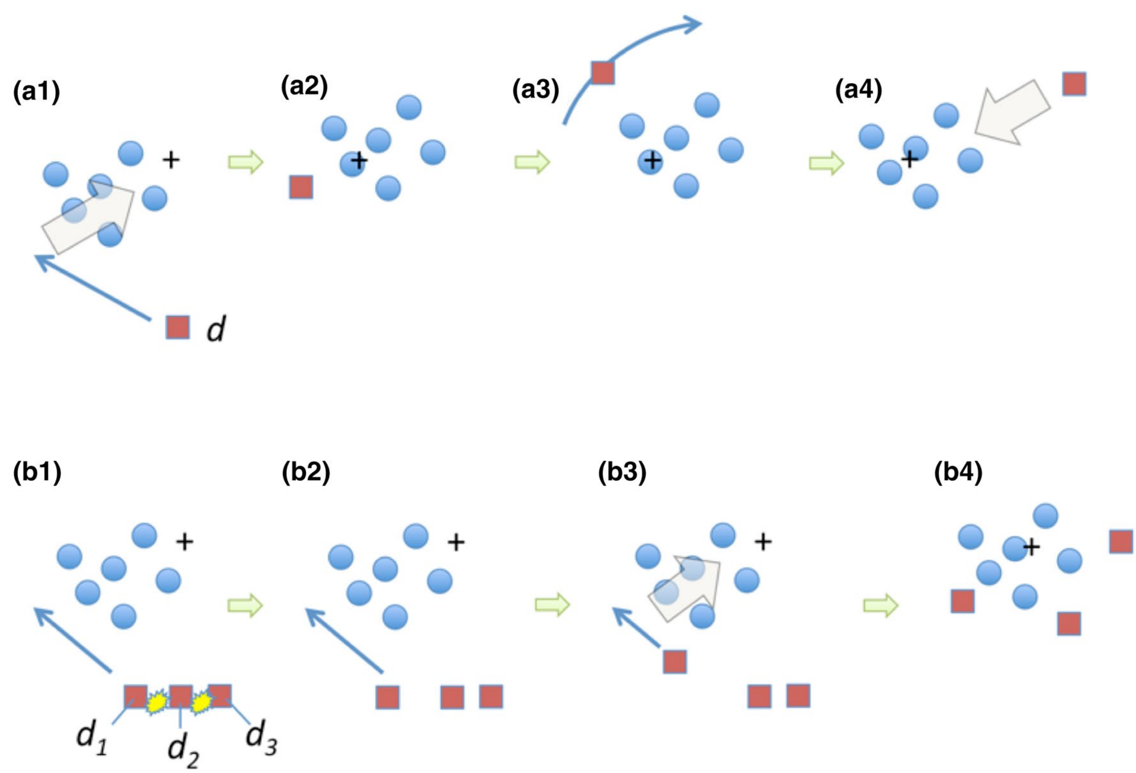

Fig. 4 Circle formation by the proposed Sheepdog agents

3. Generate the input of the control. For the edge (j, i) corresponding to the value ignored in step 2, set the elements of the adjacency matrix A to $a_{ij}[k] = 0$.

The normal agent ignores the information received from its neighbors that may be problematic. Specifically, it ignores f large ones and f small ones for each of them. Here, f is used as a parameter of the algorithm. In this case, the update rule executes consensus algorithms on the graph $G[k]$ consisting of the edges not ignored by the agent.

3 The proposed confidence-based MSR algorithm

In this section, following the MSR algorithm, the normal sheepdog agent calculates a confidence of each of the other sheepdog agents. Then, the sheepdog agent decides its own behavior by excluding the sheepdog agent with low confidence, aiming to build a system that is robust against anomalies. For this purpose, we propose three types of MSR sheepdog agents, called *n-dog* agent, *b-dog* agent, and *g-dog* agent, with different confidence criteria.

3.1 Sheepdogs with abnormalities to be used for evaluation

We explain the anomalous behavior due to failures and cyber hijacking that we are dealing with here. Here, we have divided sheepdog abnormalities into two categories: the first is “sheepdog with abnormal input” (Case 1). This sheepdog is a sheepdog that is expected to behave differently due to abnormalities in its observational functions, and to interfere with normal guidance. The second is “a sheepdog with an abnormal purpose”. This sheepdog is a sheepdog that tries to lead a flock of sheep to a different point than a normal sheepdog. These abnormal dogs may or may not have the same purpose. In this section we suppose all abnormal dogs have the same purpose (Case 2). In the following simulations, a total of six abnormal dog breeds will be constructed by combining these 2 cases with and without repulsion working between the abnormal dogs.

What anomalies to treat is a very important issue. First, if there is an agent nearby whose behavior is clearly an enemy or a major breakdown, it will eliminate this before getting on with the job. Here, we assume a stage after this elimination and deal with the case where it is not clear whether the agent is normal or abnormal. Therefore, we should assume that the agent's anomaly is something that could happen even to a normal agent. Case 1 assumes a sensor failure, while Case 2 assumes that the sensor and algorithm are correct, but the goal has been changed by hacking.

Of course, there are many other cases besides these two cases. However, as new cyber attack methods are invented every day, it is impossible to cover them all here. In addition, it would also be possible to coevolve anomalies by utilizing evolutionary computation algorithms and the like, meanwhile we thought it would be simpler to proceed with such an analysis in a specific case.

3.1.1 Sheepdog with abnormal input (Case 1)

As a way to implement a sheepdog with this anomaly, we propose the following method in Eq. 8. In the sheepdog agent, randomness is added to the parameters K_{f1}, K_{f2}, K_{f3}, and K_{f4} of each term. Therefore, the sheepdog with abnormal input (Case 1) tries to lead the sheep farthest from the goal to the goal G as the target $T(k)$, as in the farthest individual tracking control method, but its behavior fluctuates in this parameter change each time. In this study, we investigate the effects of weak and strong fluctuations on a normal sheepdog.

3.1.2 Sheepdog with an abnormal purpose (Case 2)

As a way to implement a sheepdog with this anomaly, we assume that the goal G is changed from (0,0) to (100, −100) in the sheepdog agent proposed in Sect. 2.2. Figure 6 shows the goal position of the sheepdog with anomalous goal (Case 2). In the following, the sheepdog with these two abnormalities is assumed to occur.

3.2 The proposed sheepdog agent to select others based on Confidence

We next propose an algorithm to be implemented in a normal sheepdog to deal with this anomaly: the s-dog agent always cooperates with all other sheepdog agents in the field of view. However, when a sheepdog with abnormal behavior is included, trusting all sheepdog agents in the field of view may reduce the overall guidance efficiency due to abnormal behavior. Therefore, we aim to prevent the loss of guidance efficiency by using the MSR algorithm, in which agents ignore agents that are different from themselves at each time (Fig. 7).

To select a normal sheepdog, we propose three types of measures of itself in the MSR algorithm, which we call confidence in the following, and name the sheepdog that performs each of them as follows. Dogs that are close to themselves (n-dog agent), dogs that are similar in direction (b-dog agent), and dogs that are similar in distance from the goal (g-dog agent) will sort the sheepdog agents according to each criterion and ignore those that are less similar to themselves. The number of dogs to ignore is f_η and the number of abnormal sheepdogs agents is A here. Next, we will explain each confidence in detail.

3.2.1 A sheepdogs that choose a dog that is close to itself (n-dog agent)

This sheepdog will trust the sheepdog agent in order of distance. Figure 5a shows the features of dogs that are close to the sheepdog agent (n-dog agent). The red circles are the n-dogs and the blue circles are the sheepdog agents excluded by the n-dogs. Here, the number of animals to be excluded is predetermined. In this case, the two sheepdogs farthest from themselves are excluded, assuming that two sheepdogs are ignored.

3.2.2 A sheepdog with a similar orientation (b-dog agent)

The sheepdog agents are trusted in order of the angle θ between the vector of their direction of travel and the vector of their direction to the goal G as seen from them. Figure 5b shows the characteristics of dogs whose direction is similar to that of b-dog agent. The red circles are the b-dogs, and the blue circles are the sheepdog agents that were excluded by the b-dogs. Here we assume a case of excluding two out of five sheepdog agents.

3.2.3 Dogs with a similar distance from the goal (g-dog agent)

This sheepdog trusts the sheepdog agents in order of the distance between itself and goal G. Figure 5c shows the characteristics of dogs with similar distances from the goal (g-dog agent). The red circles are the g-dogs and the blue circles are the sheepdog agents excluded by the g-dogs. Here, we assume that two agents are excluded from the 10 agents.

4 Computer experiments

4.1 Evaluation criteria

To quantitatively evaluate the guidance performance, the following evaluation indicators will be introduced.

The number of successful guidance E_s**(times)**

The number of trials in which all Sheep agents were within the circle of the target area (circle with center (0,0) and radius 15) within 500 seconds of starting the simulation.

Guidance time E_t **(seconds)**

The average of the number of seconds from the start of each simulation to the completion of guidance.

4.2 The case including sheepdogs with abnormal input (Case 1:Actuation related error)

The total number of Sheep agents (A-sheep) was set to $N = 1000$. As shown in Fig. 6, sheep agents (A-sheep) in the first time are deployed randomly in a square with a dot $[-15, 40]$ in the upper left corner and a side of 30. The total

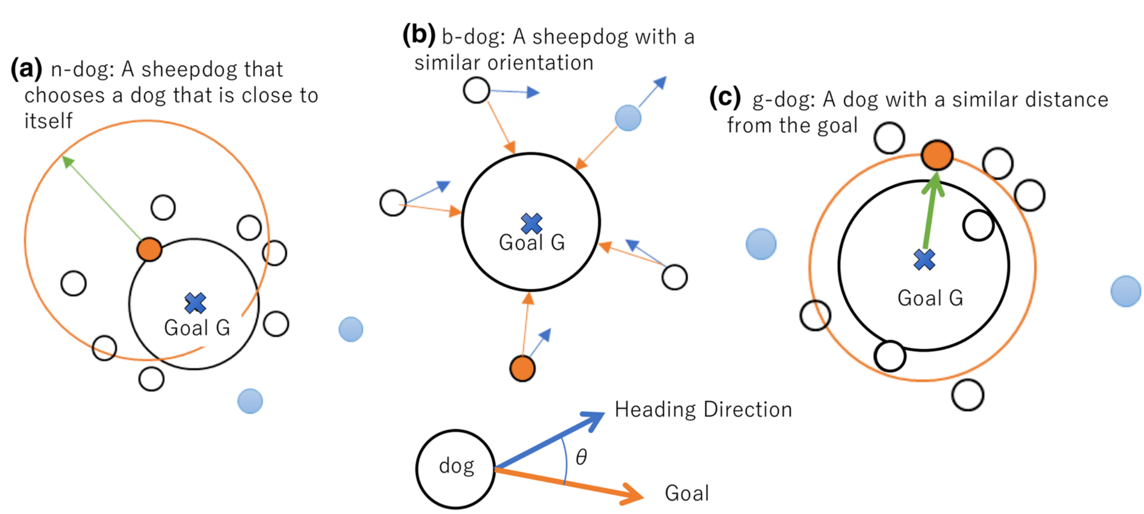

Fig. 5 MSR-dogs: **a** n-dog agent, **b** b-dog agent, **c** g-dog agent

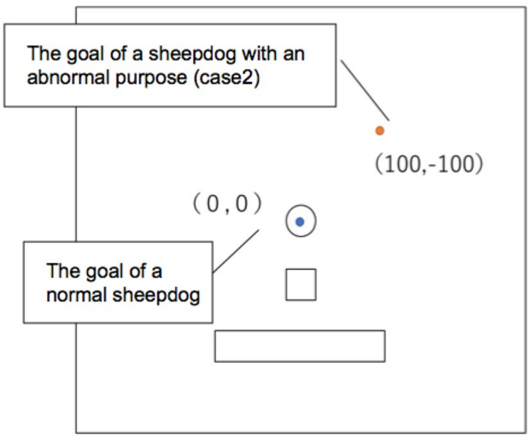

Fig. 6 Setting of the anomaly in Case 2

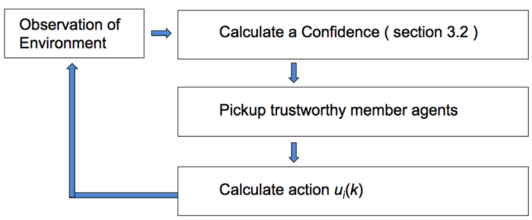

Fig. 7 The flowchart of MSR-dog agents

number of sheepdog agents is five, one of which is a sheepdog dog with an abnormal input (Case 1, $f_\eta = 1$), and the other four are normal sheepdog dogs. The sheepdog agents are also randomly deployed in a rectangle of length 30 and width 100, with the upper left corner based on the point [−50, 100]. The magnitudes of variation given to the Eq. 8 described in Sect. 3.1.1 were set to two levels, large (A1s) and small (A1w). The evaluation indices, E_s and E_t, were obtained by conducting 100 experiments with weak and strong anomalies, respectively.

The experimental results, as shown in Fig. 12, show that the MSR sheepdog agents (especially b-dog agent) can reduce the guidance time E_t when a large anomaly occurs at the input (A1s).

4.2.1 The evaluation of guidance (Case 1)

Experiments are conducted on the guidance performance of each of the four proposed sheepdog agents (s-dog, n-dog, b-dog, and g-dog), including a sheepdog with abnormal input (Case 1). The successful guidance is shown in Fig. 8, where the green square in Fig. 8 is the sheepdog with an abnormality. From the start of the simulation, the sheepdog agent surrounds the A-Sheep and guides it to the target region G. First, we can see from Fig. 9 that there is no difference in the number of successful guidance E_s among the four proposed sheepdog strategies for the sheepdog

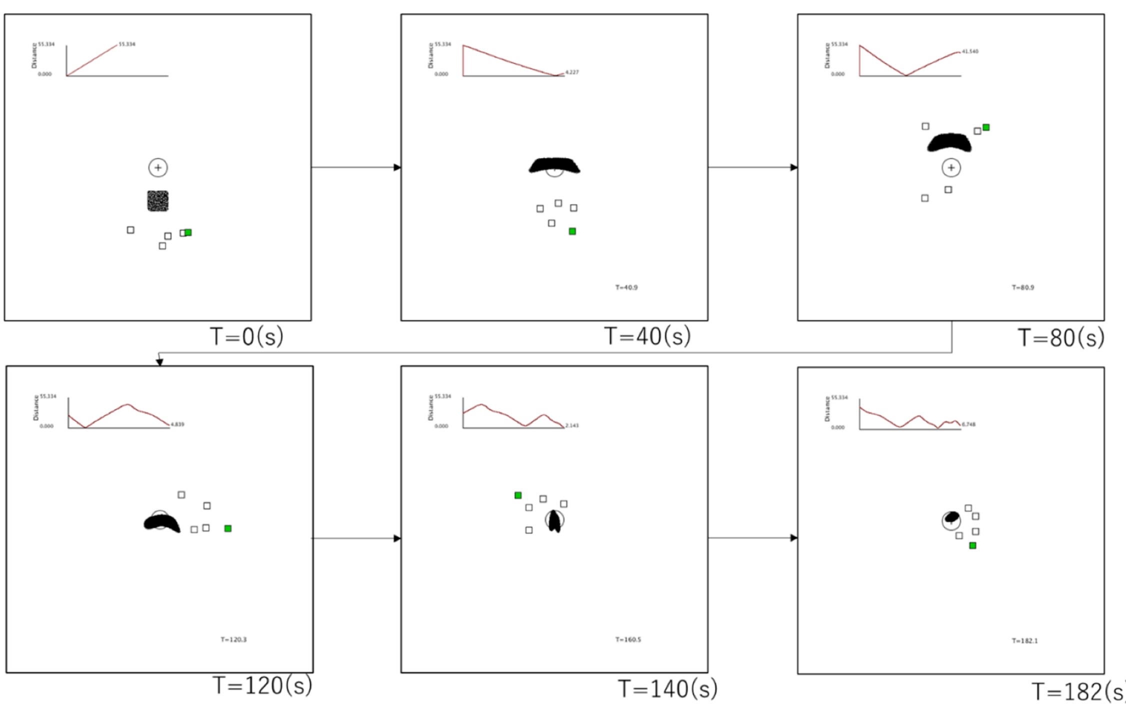

Fig. 8 Trajectory of Case 1

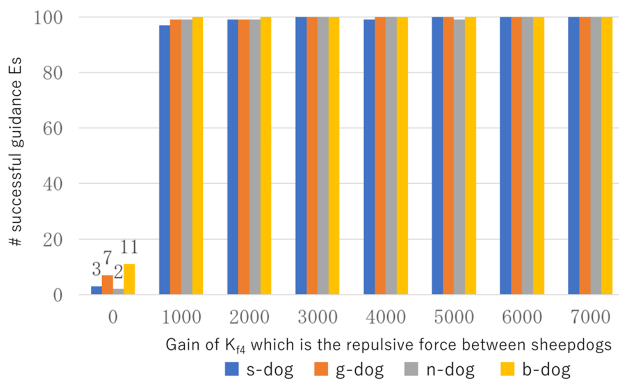

Fig. 9 E_s of Case 1w

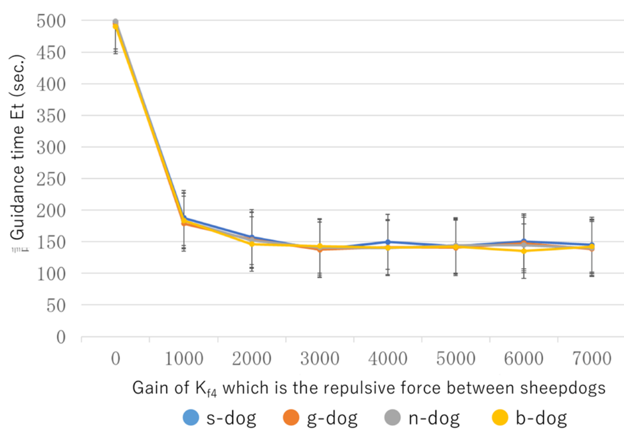

Fig. 10 E_t of Case 1w

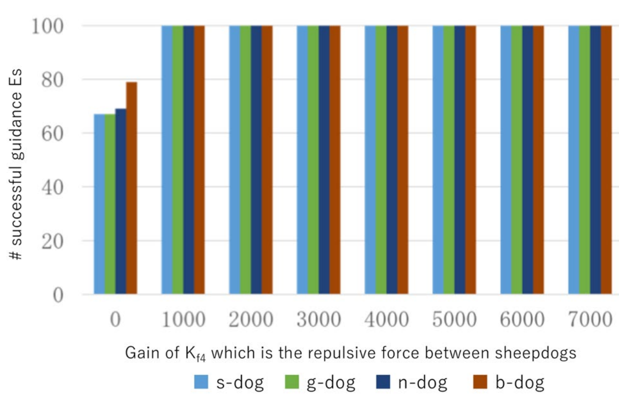

Fig. 11 E_s of Case 1

with abnormal input (Case 1). Also, from Fig. 10, there is almost no difference in the induction time Et among the four types strategies. Next, for the sheepdog with abnormal input, there is no difference in the number of successful inductions E_s among the four proposed sheepdog agents, according to Fig. 11. On the other hand, the sheepdog agents

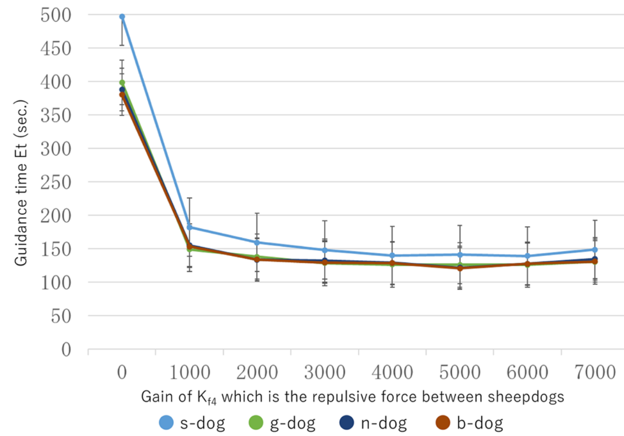

Fig. 12 Guidance time E_t of Case 1

(especially b-dog) using the MSR algorithm proposed in Fig. 12 reduced the guidance time E_t.

4.3 The case including sheepdogs with an abnormal purpose (Case 2: Different goal)

4.3.1 The detail of the settings of this experiment (Case 2)

The total number of sheep agents (A-sheep) is $N = 100$, and initially those A-sheep agents are randomly distributed in a square with a dot $[-15, 40]$ and a side of 30. The total number of sheepdogs was set at eight, four of whom were sheepdogs with abnormal objectives (Case 2) and the remaining four were normal sheepdogs($A = 4$). If there was only one sheepdog dog with Case 2, there was no significant difference in the results. Therefore we chose four sheepdogs who had an abnormal objective. Two sheepdogs are excluded from the seven sheepdogs by means of the MSR algorithm($f_\eta = 2$). The sheepdog agents are also randomly deployed in a rectangle of length 30 and width 100, with the upper left corner based on the point $[-50, 100]$. The evaluation indices, E_s and E_t, were obtained by conducting 1000 experiments.

4.3.2 The evaluation of guidance under Case 2 anomaly

We tested the guidance performance of each of the four proposed sheepdog agents (s-dog, n-dog, b-dog, and g-dog) in a situation where a sheepdog with an abnormal objective (Case 2) was mixed in. A series of consecutive snapshots of a successful guidance is shown in Fig. 13. The yellow-green square in Fig. 13 is the sheepdog with the abnormality, and the yellow–green + is the goal G of

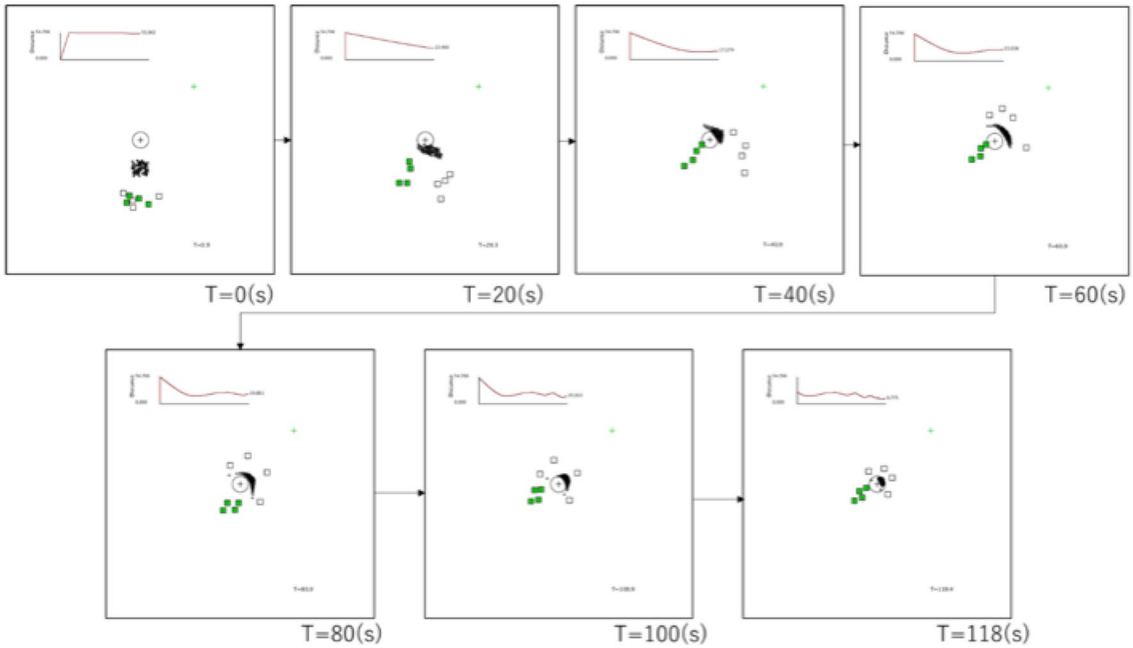

Fig. 13 A series of consecutive snapshots of a successful guidance of Case 2

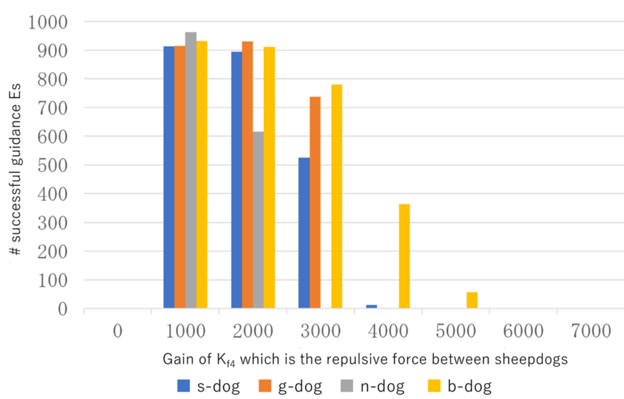

Fig. 14 The number of successful guidance E_s of Case 2

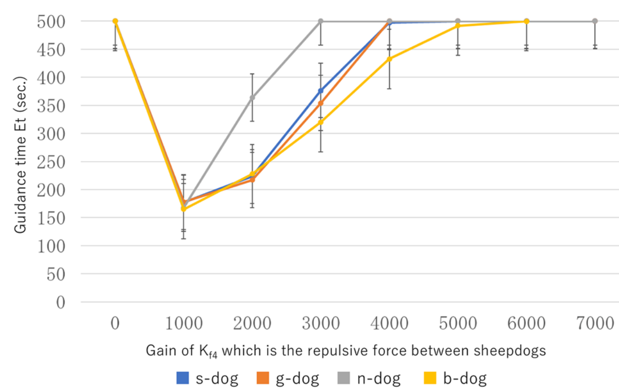

Fig. 15 Guidance time E_t of Case 2

the sheepdog with the abnormality in the objective. Figure 14 shows the relationship between E_s and K_{f4} which is repulsion force between sheepdog agents. It shows that unless K_{f4} is extremely strong, sheepdog agents (especially g-dog and b-dog) using the proposed MSR algorithm can be induced more successfully. In addition, Fig. 15 shows the relationship between E_s and K_{f4}. In terms of the induction time E_t, the shortest induction time E_t for all four types of these sheepdog agents is when the repulsion gain K_{f4} is 1000, and there is almost no difference between them. In this case, $A > f_\eta (A = 4$ and $f_\eta = 2)$, which is beyond the range where consensus is guaranteed by the original MSR algorithm. The reason why induction is possible in spite of this is considered to be that once the normal sheepdog encircles the flock, the abnormal sheepdog is no longer able to influence the group.

4.4 Scalability analysis

In this section, we investigate the scalability of the proposed method in the problem of guiding multiple sheepdogs with potentially abnormal dogs. In the case of [2, 3], it was reported that the success rate and induction time improved as the number of dogs increased in the case where no abnormalities were included. Here, we investigate the case in which a small percentage of dogs potentially contain abnormalities. We compared the success rate and induction time of s-dogs with those of s-dogs that cooperate only by repulsion without MSR, when the number of normal dogs is varied while the proportion of abnormal dogs mixed in is kept almost constant.

For the number of sheep $N = 100$, we performed the experiment for $(M, A) = \{(5, 1), (10, 2), (15, 3)\}$ where M is the number of normal dogs and A is the number of abnormal dogs. The number of dogs ignored f_η was set equal to the number of abnormal dogs A, respectively. The performances are shown in Table 1.

Four more types of abnormal dogs were added to. The total number of abnormal cases is six as follows: {a case in which errors related to input information occur (*actuatorE* in the table, corresponding to Case1 in the last experiments), a case in which each goal is different for each abnormal dog (*dgoal* in the table), and a case in which the goals of the abnormal dogs are same (*sgoal* in the table, corresponding to Case2) }× {when the repulsive force is active among the abnormal dogs ("repulsive"), when it is not active ("off") }. At least 100 trials were conducted for each of them, and the number of successful induction E_s is shown in the upper box and the induction time E_t is shown in the lower box of each column of the table.

Those with more rapid E_t than s-dogs are indicated by green boxes. For example, in the bottom row of "actuatorE" of the middle of Table 1, the row of "repulsive", and the column of "g-dog", the top row is 1 and the bottom row is green at 294.01, which means that when the number of normal dogs M is 10 and the number of abnormal dogs $A = 2$ (when there is repulsive force even among abnormal dogs), the induction is 100% successful and the average the induction time E_t is 294.01 seconds, indicating that the induction is more rapid than the s-dog's 354.00 sec. In all cases, as the number of normal dogs increases, the induction time is reduced even when a small percentage of abnormal dogs are mixed in.

Almost all of the three tables are green, indicating that within this range, the proposed MSR method has a higher inductive performance against anomalies than the s-dog with only repulsion. However, the proposed MSR method performs worse than s-dog agent in the cases of "dgoal" with repulsive force and "sgoal" with no repulsive force strategy. The common feature of these two cases is that the proposed method is able to induce the dogs extremely quickly in all normal dog strategies. However, in the former case, the abnormal dogs tend to be geographically dispersed, while in the latter case, the abnormal dogs tend to overlap in one place and become twice as strong. Thus, the characteristics of the two are very different. The analysis of the two is a subject for future work.

4.5 Sensitivity analysis of number of dogs to ignore f_η

In this section, we investigate the performance of the proposed MSR method when the number of dogs to ignore is somewhat different from the actual number of anomalies. When the number of dogs to be ignored is smaller than the actual number of abnormal dogs, even if an abnormal dog is successfully detected, some other abnormal dogs will be included in the member used as a norm for decision making. On the other hand, if we ignore too many dogs, dogs may lack the information necessary for appropriate cooperation. Therefore, it is desirable for the sensitivity to this parameter to be robust. We investigated the relationship between the performance and the number of dogs to be ignored, A, under a constant number of abnormal dogs.

The results are shown in Table 2. Here, the number of sheep is $N = 100$, the number of normal dogs is $M = 5$, and the number of abnormal dogs is $A = 2$. This environment is more difficult than the previous experiment with one more abnormal dog. The number of dogs to ignore is f_η here. In the following, we experimented with $f_\eta = \{1, 2, 3\}$. These result are shown in the top, the middle, and the bottom tables of Table 2, respectively. In each column, the ratio of successful inductions E_s is shown in the upper box, and the induction time E_t is shown in the lower box. Those with E_t faster than s-dog are shown in the green frame. The difference from Table 1 is red numbers, which represents the fastest average induction time E_t in f_η. For example, when using the b-dog strategy for an abnormal dog that takes the ("dgoal", "off") strategy, the shortest induction time E_t is 232.74 and also it can be read that the case is $f_\eta = 2$.

In the middle table with $f_\eta = 2$, almost all cases could be induced more quickly than s-dog even in an environment with an abnormal number of potential dogs. In addition, cases of $f_\eta = 2$ were able to guide the dog in the shortest time in $4/9(= 8/18)$ cases in the same-strategy with $f_\eta = 1, 3$, indicating that it is better to ignore the number of dogs consistent with the actual situation.

In the previous experiment, the number of green boxes in the table $(M, A) = (5, 1)$ is 7 out of 9, whereas in the present experiment, the most number of green boxes is 8 out of 9 for the case where the repulsive force is off. (In all cases, the highest number is 17 out of 18). This result suggests that the proposed method may be more effective in more difficult situations when the total number of dogs is small.

On the other hand, even when $f_\eta = 1, 3$, which is different from the actual situation, almost all cases were able to induce dogs more quickly than s-dogs even in an environment with an abnormal number of potential dogs, and no drastic performance degradation was observed. Also, when $f_\eta = 1, f_\eta < A$. In this case, all of the failed dog agents cannot be removed, but the reason why the effect is still seen is because the circle formation could be achieved with normal ones, as in the case of Sect. 4.3.2. However, for the ("sgoal", "off") strategy, the average guidance time E_t deteriorated for $f_\eta = 1, 3$, and especially for $f_\eta = 3$, the performance deteriorated for all proposed strategies. This anomalous dog

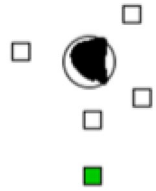

Fig. 16 Exclusion

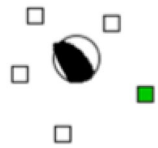

Fig. 17 Cooperation

Table 1 Scalability Analysis: Performance of different size of sheepdogs with anomalies

M=5,A=1,f_η=1		b-dog	g-dog	n-dog	s-dog
actuatorE	repulsive				
	off	1.00	1.00	1.00	1.00
		705.92	349.15	352.37	725.92
dgoal	repulsive				
	off	1.00	1.00	1.00	1.00
		298.42	293.75	271.00	307.57
sgoal	repulsive				
	off	1.00	1.00	1.00	1.00
		208.95	201.89	210.04	208.59

M=10,A=2,f_η=2		b-dog	g-dog	n-dog	s-dog
actuatorE	repulsive	1.00	1.00	1.00	1.00
		296.60	294.01	290.15	354.00
	off	1.00	1.00	1.00	1.00
		601.29	296.08	290.57	601.51
dgoal	repulsive	1.00	1.00	1.00	1.00
		172.92	161.98	171.58	161.57
	off	1.00	1.00	1.00	1.00
		163.60	171.81	175.08	178.56
sgoal	repulsive	1.00	1.00	1.00	1.00
		170.82	175.52	170.40	177.57
	off	1.00	1.00	1.00	1.00
		169.53	174.40	168.15	172.83

M=15,A=3,f_η=3		b-dog	n-dog	d-dog	s-dog
actuatorE	repulsive	1.00	1.00	1.00	1.00
		286.81	284.77	283.73	288.13
	off	1.00	1.00	1.00	1.00
		290.01	286.44	283.01	289.45
dgoal	repulsive	1.00	1.00	1.00	1.00
		140.30	140.52	140.19	139.00
	off	1.00	1.00	1.00	1.00
		141.73	131.38	137.21	131.79
sgoal	repulsive	1.00	1.00	1.00	1.00
		166.27	168.16	165.98	168.09
	off	1.00	1.00	1.00	1.00
		162.20	164.29	162.41	163.70

$N = 100$. top $M = 5,\ A = 1,\ f_\eta = 1$, middle $M = 10,\ A = 2,\ f_\eta = 2$, bottom $M = 15,\ A = 3,\ f_\eta = 3$

group overlaps all of them because the repulsive force does not work. This is equivalent to a single dog whose action is twice as strong as the number of dogs, suggesting that the proposed method requires cooperation with an appropriate number of dogs to prevent this anomaly.

Table 2 Performance for different f_η values

M=5,A=2,f_η=1		b-dog	g-dog	n-dog	s-dog
actuatorE	repulsive	1.00	1.00	1.00	1.00
		356.90	351.05	355.42	359.72
	off	1.00	1.00	1.00	1.00
		354.78	349.60	352.52	367.26
dgoal	repulsive	1.00	1.00	1.00	1.00
		254.13	260.36	242.24	323.82
	off	1.00	1.00	1.00	1.00
		260.18	236.87	246.96	272.50
sgoal	repulsive	1.00	1.00	1.00	1.00
		201.02	208.31	208.89	226.17
	off	1.00	1.00	1.00	1.00
		203.07	213.54	201.51	203.11

M=5,A=2,f_η=2		b-dog	g-dog	n-dog	s-dog
actuatorE	repulsive	1.00	1.00	1.00	1.00
		353.28	343.31	334.91	359.72
	off	1.00	1.00	1.00	1.00
		361.94	351.56	384.12	367.26
dgoal	repulsive	1.00	1.00	1.00	1.00
		242.76	230.08	210.47	323.82
	off	1.00	1.00	1.00	1.00
		232.74	250.21	245.90	272.50
sgoal	repulsive	1.00	1.00	1.00	1.00
		202.85	203.36	208.19	226.17
	off	1.00	1.00	1.00	1.00
		200.95	191.92	194.84	203.11

M=5,A=2,f_η=3		b-dog	g-dog	n-dog	s-dog
actuatorE	repulsive	1.00	1.00	1.00	1.00
		356.21	362.08	330.46	359.72
	off	1.00	1.00	1.00	1.00
		352.88	357.59	377.18	367.26
dgoal	repulsive	1.00	1.00	1.00	1.00
		261.38	253.59	265.26	323.82
	off	1.00	1.00	1.00	1.00
		255.33	249.77	236.60	272.50
sgoal	repulsive	1.00	1.00	1.00	1.00
		193.08	198.31	193.95	226.17
	off	1.00	1.00	1.00	1.00
		211.14	287.46	295.09	203.11

($N = 100$. top:$f_\eta = 1$, middle:$f_\eta = 2$, bottom:$f_\eta = 3$)

4.6 Summary of experiments

In this paper, we proposed sheepdog agents that use MSR algorithm to select a companion based on its similarity to itself. In the first experiment, we conducted an experiment to clarify the effect of the proposed method. Experiments show that the MSR-sheepdog agents improve the guidance efficiency in both the case of a sheepdog with an abnormal input (Case 1) and the case of a sheepdog with an abnormal goal (Case 2). Next, we investigated the scalability of the proposed method and the proportion of dogs to be ignored in the MSR method by expanding the number of abnormal dogs to six types. As a result, the following results were obtained.

In sheepdogs with abnormal inputs (Case 1), the guidance time E_t was reduced by sheepdog agents (especially b-dogs) using the proposed MSR algorithm. This is because the dog (b-dog) selected by similarity in direction had the best induction efficiency, although only slightly, because each gain of the abnormal sheepdog agent would go in a strange direction if it was determined randomly.

When sheepdog dogs with abnormal purpose (Case 2) are in, sheepdog agents (especially b-dog and g-dog) can guide their sheep herd more. On the other hand, the time required for guidance was almost the same as that of the conventional method, s-dog.

Based on the results of these two experiments, there are two cases in which the proposed counter-strategy has an effect on the success rate or on the induction time. This is probably related to the way of cooperation, i.e., exclusion (Fig. 16) or "join only when it is good" type (Fig. 17).

Next, we examined the scalability of the proposed method. For all anomalies, the success rate and induction time improved as the total number of dogs increased, even if a certain percentage of anomalous dogs were mixed in. This suggests that operating a large number of agents is also useful for security in the siege/guidance problem. Also varying the number of sheepdogs into four patterns $(M, A) = \{(5, 1), (5, 2), (10, 2), (15, 3)\}$, and we comprehensively investigated four different counter-strategies. The results showed that the proposed MSR method was generally effective within the scope of this study.

Also it was found that the proposed MSR method may not be effective when dogs with abnormalities gather in one place and become a powerful abnormal dog. This issue needs to be considered in the future. Also this study discusses a relatively healthy case in which a small number of abnormal dogs occur in a group of normal dogs, and more serious cases should be considered in the future. This is also an issue to be addressed in the future.

5 Conclusions

In this paper, we propose a method for efficiently guiding a large number of sheep agents through the cooperation of multiple sheepdog agents even in the presence of abnormalities, and verify its performance in computer experiments. The results show that the MSR algorithm can guide a group of sheep agents more efficiently and reliably than the conventional method, even when the group includes sheep dogs with abnormalities.

In this paper, no mathematical verification has been done. This is a subject for future work.

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