Demonstrating the Differential Impact of Flock Heterogeneity on Multi-Agent Herding*

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Abstract. This paper explores the differential impact of multi-agent system heterogeneity in the context of an idealised herding task. In simulation, a team of simple herders must move a flock towards a target location in a continuous 2d space. Flock heterogeneity is controlled by dividing the flock into a number of non-overlapping social groups that influence sheep movement. Results demonstrate that increasing system heterogeneity (i.e., the number of different social groups) *reduces* herding performance when social groups are self-attracting, but conversely, the same increase in system heterogeneity can *increase* herding performance when groups are other-attracting. Implications for designing heterogeneous multi-agent systems are considered.

Keywords: Heterogeneous · Multi-agent · Herding

1 Introduction

Intelligent systems comprising some combination of robots, humans and software agents promise to deliver increased flexibility and efficiency by sharing and coordinating their resources, information and capabilities. However, designing these multi-agent systems (MAS) brings considerable challenges. Their control may be decentralised to some extent, they may need to operate in noisy and uncertain environments, and finally the different agents involved may need to be designed (and to operate) without complete knowledge of the way in which other agents in the system have been designed or are operating. Consequently, the challenge of engineering these systems is strongly influenced by the extent to which the agents involved exhibit *heterogeneity* of different kinds.

A heterogeneous MAS involves agents that are different from each other, e.g., a team of human carers working alongside robot care assistants to deliver services to patients [1], or the coordination of aerial and ground based robots to map the surface of Mars [11]. Such heterogeneity may arise for many reasons: team diversity may be required in order to satisfy multiple functional requirements; mixing sub-systems with different provenance or legacy issues may be

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unavoidable; agents with differing degrees of degradation or component failure may be expected to inter-operate, etc.

Achieving systems such as these will require engineers to design solutions that exploit the positives of system heterogeneity while mitigating any negatives. This will require better understanding of when and how heterogeneity impacts system performance. This paper characterises the differential impact of agent heterogeneity on system performance in a simple multi-agent setting. A team of artificial dogs, driven by simple reactive controllers, are tasked with herding a flock of sheep that exhibit a parameterisable degree of heterogeneity. The paper's key contribution is to characterise the way in which the positive and negative impact of this heterogeneity differs with aspects of the agent's social structure.

1.1 Motivation

Heterogeneity has been studied extensively in social systems. In books such as *The Difference* [16] and *The Wisdom of Crowds* [20] it is argued to be a positive, as diverse views and strategies inject useful resilience and redundancy into human systems. By contrast, heterogeneity is typically regarded as an unwanted feature of engineered systems, where uniformity and regularity are associated with predictable and reliable performance. Perhaps consequently, the value of heterogeneity for artificial autonomous systems is not clear cut.

On the one hand, the Law of Requisite Variety tells us that a more heterogeneous system requires a more complex controller [12]. This reinforces the belief that heterogeneity is strongly associated with complexity, and something engineers want to avoid in order to create reliable systems. On the other hand, the El Farol Bar problem suggests a diverse, heterogeneous system performs better [2]. It can be seen as an allegory for the view that *homo*geneous systems can be brittle; if one element has a vulnerability then all have a vulnerability.

The dual nature of heterogeneity poses a problem for the design of autonomous robotic systems. Just when is heterogeneity helpful and when is it harmful? There is a lack of prior work which investigates this specific question, particularly within a single task domain. This prevents direct comparisons which makes it difficult to understand how heterogeneity could affect a system.

1.2 Related Work

An important step to understanding MAS heterogeneity is to devise a means to measure it. In [4], concepts from taxonomy are drawn on in order to measure heterogeneity in terms of dendrograms and social entropy. Both [4] and [21] present means to measure differences between agents in terms of distance norms. Distance norms and entropy seem common ways of characterising heterogeneity but it is rare to see measures of heterogeneity linked to performance. An exception is [6]. An evolutionary framework and heterogeneity measure are developed based on agent fitness. These are then used to show that heterogeneous agents suited a travelling mailman task but homogeneous agents suited a foraging task.

In similar work, [4] shows via reinforcement learning that a single policy suited foraging but agents with different policies were better at playing robot soccer.

The natural world is often used as a source of inspiration when discussing heterogeneity. The work of [14] demonstrated through simple modelling that having a mix of age and mass can improve the success of wolf pack hunting. In [23], artificial evolution was used to create teams of heterogeneous and homogeneous agents which were tested on tasks requiring different amounts of cooperation. A framework for human MAS is used in [16] to show that, provided certain conditions are met, a heterogeneous system of lesser agents performs better in problem solving than a homogeneous system of superior agents.

Perhaps the most pertinent question for a MAS designer is how to exploit heterogeneity to benefit performance. To this end, exploiting heterogeneity can be viewed as a resource allocation problem, for examples see [8,9,17]. While effective, these prior works only consider heterogeneity in the scope of functional capability. While it could be concluded that the weight of prior work views heterogeneity as positive, there are exceptions. In [5], the author comments that trials with heterogeneous agents were not successful because agents reacted differently to the same stimulus. This led to confused behaviour at the population level and poor overall performance.

Overall, the majority of prior work studies heterogeneity as a means to solve a given task. General design principles for heterogeneity are rarely, if ever, proposed. Consequently, there remain unanswered questions concerning when and how heterogeneity (or homogeneity) should be employed by a MAS designer. This paper presents a comparative analysis of heterogeneity in the context of a single multi-agent herding task, demonstrating that its effect on performance can change from negligible to significant as only a single parameter is varied, and showing that heterogeneity can be beneficial or detrimental to performance in a manner that depends on subtle changes to agent behavioural rules.

2 Model

Herding is a multi-agent task in which one or more herding agents attempts to influence a second group of herded agents towards a goal. Here we use a common formulation of the task in which a number of "dog" agents are tasked with moving a number of "sheep" agents to a target location. The task has been studied by a number of different authors. This paper uses a relatively traditional model however there are number of alternatives, for example applying the unicycle model to the dogs [18], encircling the flock with relatively many dogs and then moving them in formation towards the goal [15], or using a motion control strategy for the dogs based on goal occlusion by the flock [10].

2.1 Experimental Setup

The work by [22] is widely regarded as one of the earliest in the area. In their research, a single robot sheepdog herds a flock of geese in an enclosed pen. [19]

took this a step further and their paper typifies the traditional approach: the herding strategy adopted by a dog is split into separate collecting and driving phases, and the dog uses heuristics to choose steering points from which to influence the sheep. A solution to the problem of reaching these steering points without adversely affecting the flock is provided by [13] and [7].

The work here makes a number of contributions to this traditional model. It uses Voronoi partitioning [3] to subdivide the task of gathering the flock amongst multiple dogs. Previous works, [7,13], suggests a planning based controller, here, a simple reactive behaviour is described that accomplished the same task (to our knowledge for the first time). Finally, each sheep belongs to a social group that is influenced by a target group (either itself or a different group). This influence may be a positive bias (sheep inside this target group are attractive) or a negative bias (sheep outside this target group are attractive).

This simulation is conducted as follows within a 2D space measuring 400 by 400. Thirty sheep are initially distributed over a 270 square region centred on the point (200,220) using a uniform random distribution. Two dogs aim to move all the sheep to within a threshold distance of a goal located at (40,30) in minimum time. The goal and starting locations of the dogs remain the same throughout the experiments. A two phase strategy first collects the sheep together into a single group and then drives the flock to the goal. A single herding episode lasts 2000 time steps and results are averaged over 50 episodes to reduce the effect of random initial conditions.

For each time step, an acceleration is calculated for each agent, based on virtual forces that are influencing it at that instant. Each agent's velocity is updated according to their new acceleration, and their new positions are calculated. A physics check tweaks the simulated positions of two agents if they occupy the same space. The dogs can always see all the sheep, and the experiment was repeated for sheep with a small (60) and large (600) visible range.

2.2 Sheep Agent Model

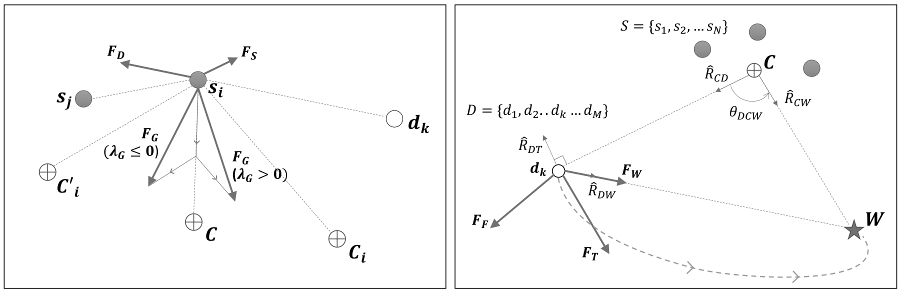
Each sheep experiences a weighted combination of three virtual forces (Fig. 1a) exerted by agents within their visual range: repulsion from visible dogs (F_D), very short range repulsion from any other sheep (F_S), and a longer range social attraction to other sheep (F_G).

$$F = K_D F_D + K_S F_S + K_G F_G \tag{1}$$

Here, $K_D = 20$, $K_S = 200$ and $K_G = 1$, and are parameters governing the strength of the influence of each of the three force. The forces are determined as follows:

$$F_D = \sum_{k}^{D} \frac{s_i - d_k}{\|s_i - d_k\|} e^{-\lambda_D \|s_i - d_k\|} \tag{2}$$

$$F_S = \sum_{j \neq i}^{S} \frac{s_i - s_j}{\|s_i - s_j\|} e^{-\lambda_S \|s_i - s_j\|} \tag{3}$$



(a) (b)

Fig. 1: The virtual forces acting on (a) a sheep, s_i, and (b) a dog, d_k, where C is the overall flock centre of mass, C_i is the centre of mass for visible sheep in s_i's preferred social group, and C'_i is the centre of mass for sheep that are outside this group, W is the dog's current steering point, $\hat{R}_{CD}$, $\hat{R}_{CW}$, $\hat{R}_{DW}$ and $\hat{R}_{DT}$ are unit vectors, and $S = \{s_1, s_2 \ldots s_N\}$ is the set of visible sheep.

$$F_G = \begin{cases} \lambda_G \frac{C_i - s_i}{\|C_i - s_i\|} + (1 - \lambda_G) \frac{C - s_i}{\|C - s_i\|} & \text{if } \lambda_G > 0 \\ \\ |\lambda_G| \frac{C'_i - s_i}{\|C'_i - s_i\|} + (1 - |\lambda_G|) \frac{C - s_i}{\|C - s_i\|} & \text{if } \lambda_G <= 0 \end{cases} \tag{4}$$

where D and S are the set of visible dogs and visible sheep respectively, λ_D and λ_S are set to 0.1 & 0.6 respectively and determine the length scale of the two repulsive forces. The social grouping mechanic uses three centre of mass: C, C_i and C'_i. These are the centres of mass for (i) all visible sheep, (ii) all visible sheep in i's target social group and, (iii) all visible sheep not in i's target social group, respectively. Centres of mass are always calculated as the average position of a set of sheep, given by $\sum s_j/N$, where N is the number of sheep in the set.

The influence of a sheep's target social group is governed by two parameters: the identity and location of the visible group members, and the social bias towards the group, denoted λ_G. This bias controls the degree of *heterophily* $(-1 < \lambda_G < 0)$ or *homophily* $(0 < \lambda_G < 1)$ displayed by the sheep. When $\lambda_G = 0$ sheep are influenced by group members and non group members indiscriminately.

2.3 Dog Agent Model

The strategic part of the Dog model follows that specified in [19] to identify steering points as locations for the dogs to move towards. Initially, during the *collecting* phase each dog chooses a steering point to target a peripheral sheep, i.e., the one furthest from the flock's centre of mass (CoM), and drives it towards the flock's current CoM. Once all sheep are within a threshold distance, d, of the CoM, the dogs transition from collecting to *driving*. During the driving phase, the dogs move the flock towards the goal by choosing a steering point which is colinear with the goal and the flock CoM. A dog will re-collect any sheep that strays further than $1.6d$ from the CoM during driving. The dogs have a visible range of 600.

To enable multiple dogs to coordinate their activities, the space occupied by the flock is partitioned into Voronoi cells seeded with the location of the dogs. This partitioning is performed at a global level. During the collecting phase, each dog targets a succession of the most peripheral sheep within its own cell. A single dog is then chosen to drive the flock during the driving phase while the other dogs hold a position away from the flock (unless and until a sheep strays too far from the flock).

A dog's movement between steering points in controlled by a reactive controller comprised of two behaviours: a force to interact with the sheep (F_H) and a repulsive force to avoid getting too close to other dogs (F_D). The resultant behaviour is a weighted vector of these forces:

$$F = K_H F_H + K_D F_D \tag{5}$$

where $K_H = 1$ and $K_D = 10$.

The repulsion, F_D, is designed to causes the dog (d_k) to rotate around another dog (d_j) rather than simply be repulsed. This creates a graceful way of handling deadlock situations and is modelled as:

$$F_D = F_{DD} + 0.75 F_{\perp DD} \tag{6}$$

where:

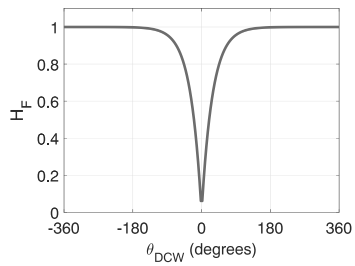
$$F_{DD} = \sum_{j \neq k}^{D} \frac{d_k - d_j}{\|d_k - d_j\|} \tag{7}$$

The herding force, F_H, is a weighted combination of 3 behaviours: Repulsion from sheep (F_F), attraction towards the current steering point (F_W), and an orbital force around the flock (F_T). These behaviours interact to cause the dog to move around the flock, towards the steering point, at a sufficient distance from the sheep to leave them undisturbed. As the dog approaches the steering point, the repulsion to the sheep rolls off and it moves closer to interact with its target sheep. The forces are combined via the equation:

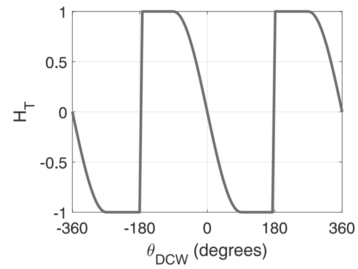
$$F_H = K_F F_F + K_W F_W + K_T F_T \tag{8}$$

where $K_F = 20$, $K_W = 2$, and $K_T = 8$.

The herding behaviours in equation 8 are a function of the dog position d_k, the positions of the sheep $S = \{s_1 ... s_N\}$, and the angular error (θ_{DCW}) between the dog's desired and current approach directions (Fig. 1b). The component forces are calculated as:



(a)



(b)

Fig. 2: a) The roll off in sheep repulsion force, $H_F = 1 - e^{-2|\theta_{DCW}|}$, as the dog approaches its steering position, . b) The magnitude of the orbital force rolls off as the angle between the ideal and current approach direction decreases. The sign ensures the dog takes the shorter orbital direction around the flock.

$$F_F = H_F(\theta_{DCW}) \sum_i^S \frac{d_k - s_i}{2\|d_k - s_i\|} \tag{9}$$

$$F_W = \hat{R}_{DW} \tag{10}$$

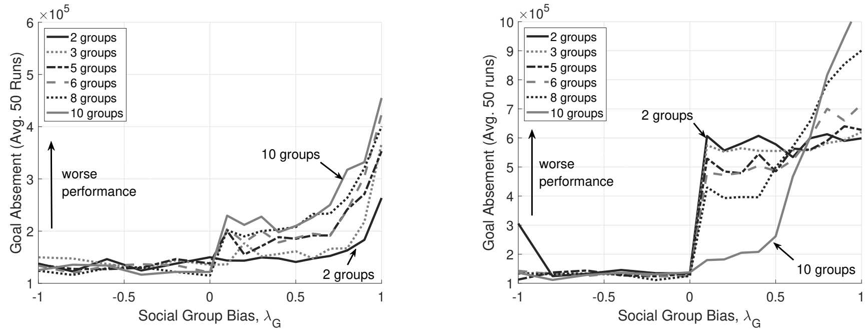
$$F_T = H_T(\theta_{DCW}) \hat{R}_{DT} \tag{11}$$

$H_F(\theta_{DCW})$ rolls off the sheep repulsion as the dog lines up with its steering point. The form of $H_F(\theta_{DCW})$ is given in Figure 2a. The orbital force (F_T) acts tangentially to the flock circumference, and its magnitude is controlled by $H_T(\theta_{DCW})$ which, similar to the sheep repulsion, rolls off as the dog approaches its steering point. The form of $H_T(\theta_{DCW})$ is shown in Figure 2b.

3 Results

The following results characterise the performance of the multi-agent herding system as we vary three aspects: i) the number of different sheep social groups, ii) the nature of the social group bias, and iii) whether a sheep's target social group is its own group, or a different group. System performance is measured in terms of minimising goal absement, i.e., minimising the distance between the goal location and the centre of mass of all sheep, C, integrated over time. While this doesn't capture the cohesion of the flock explicitly, it proved to be a reliable indicator of how difficult the task was to complete.

Figure 3a shows results for scenarios in which a sheep's own social group is also its target social group. When sheep are attracted towards members of this social group (*homophily*, $\lambda_G > 0$), the performance of the system degrades as heterogeneity increases. That is, the more social groups exist within the flock, the harder the flock is to herd. By contrast, when each sheep is attracted to



(a) Self attraction rules

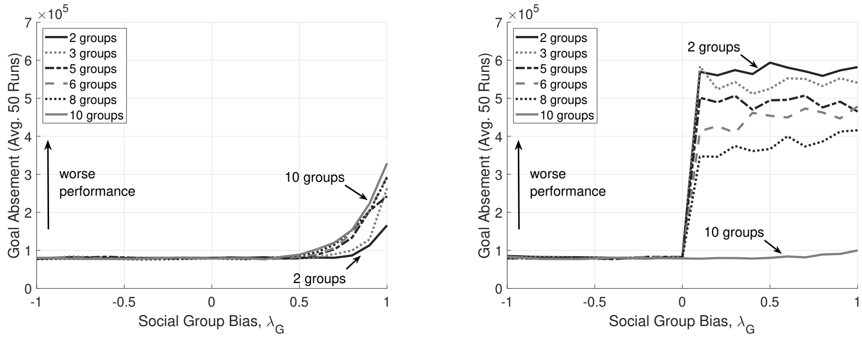
(b) Ring attraction rules

Fig. 3: Herding performance under two flock social structures: a) sheep are influenced by their own social group, b) sheep are influenced by another social group. In both cases, negative social bias extinguishes the effects of heterogeneity. However, under positive social bias, increasing heterogeneity helps or hinders performance depending on the flock social structure.

flock members outside its target social group (*heterophily*, $\lambda_G < 0$), the impact of heterogeneity is extinguished. This makes flocks easy to herd regardless of the social structure within the flock. These results can be explained by noting that heterophily tends to encourage mixing of the flock's social groups resulting in global cohesion, whereas homophily tends to encourage each social group to form a sub-flock, reducing the overall global cohesion of the flock and thereby making it more difficult to herd. Increasing the number of types exacerbated this effect of homophily. In summary, when agents are attracted to their own group, heterogeneity has a negative effect on performance, but this does not hold when agents exhibit heterophilic behaviour.

Figure 3b depicts an analogous set of results for the herding system where a sheep's target social group is not its own but instead one other social group in the flock. The target social group is determined according to a ring arrangement. For n social groups, G_1, G_2, through G_n, members of group G_i are influenced by members of G_{i+1} and members of group G_n are influenced by members of G_1. The nature of the influence may be positive (each sheep is attracted towards members of its target group, $\lambda_G > 0$) or negative (each sheep is attracted towards sheep that are not members of its target group, $\lambda_G < 0$).

Under these conditions, the impact of heterogeneity changes. As before, for $\lambda_G < 0$ performance is not influenced by heterogeneity, with herding being easy regardless of the number of social groups within the flock. However, where $\lambda_G > 0$ (i.e., sheep are attracted to their target social group), increasing heterogeneity can either improve performance (when social bias is weak, $0 < \lambda_G \lesssim 0.6$), or decrease performance (when social bias is strong, $0.6 \lesssim \lambda_G < 1.0$). The interaction between positive social bias and heterogeneity can be explained by noting that strongly positive social bias means sheep are strongly attracted to



(a) Self attraction rules

(b) Ring attraction rules

Fig. 4: As Figure 3 except sheep vision range is increased from 60 to 600.

their target group CoM, C_i. A large number of groups and the fixed population size means only a small number of sheep are in each group. This, combined with the limited visible range (60), creates circumstances where sheep in the same social group calculate different C_i's which causes the flock to fragment. This does not occur when the social bias is weekly positive due to sheep being attracted to the CoM of all visible sheep, C, which is more consistent across a group of sheep. Consequently, results for sheep with a much larger sensor range extinguish this effect (Fig. 4). Note also that while the differences in performance depicted in Figure 3a could be attributable to a difference between the number of sheep inside and outside each social group, the contrast between Figure 3a and Figure 3b cannot be so attributed as the number of members within social groups is equivalent between these two sets of results, indicating that it is the nature of the flock heterogeneity that is accounting for performance differences.

4 Conclusions

By characterising how the performance of a relatively simple multi-agent system changes as system heterogeneity is varied, both in terms of its magnitude and character, we have shown that understanding whether heterogeneity will be a positive or negative influence on multi-agent systems is a subtle question. Simply knowing whether or not a system is heterogeneous, or knowing the amount of heterogeneity exhibited by a system is not enough to anticipate MAS design challenges or guide good MAS design decisions. A deeper understanding of the link between heterogeneity and multi-agent system dynamics is needed. Future work will take this a step further by investigating the effect of functional heterogeneity, such as movement speed and sight range, on the herding problem.

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