

Tracking Footprints in a Swarm: Information-Theoretic and Spatial Centre of Influence Measures

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Abstract—Boids (bird-oids) is a widely used model to mimic the behaviour of birds. Shoids (sheep-oids) rely on the same boids rules with the addition of a repulsive force away from a sheepdog (a herding agent). Previous work assumed homogeneous shoids. Real-world observations of sheep show non-homogeneous responses to the presence of a herding agent. We present a portfolio of information-theoretic and spatial indicators to track the footprints of shoids with different parameters within the shoid flock. The portfolio is named the Centre of Influence to indicate that the aim is to identify the influential shoids with the highest impact on flock dynamics. We use both synthetic simulation-driven data and measurements collected from live sheep herding trials by an unmanned aerial vehicle (UAV) to validate the proposed measures. The resultant measures will allow us in our future research to design more efficient control strategies for the UAV, by polarising the attention of the machine learning algorithm on those shoids with influence footprints, to drive the flock to improve the herding of sheep.

Index Terms—Centre of Influence, Predation Risk, Situation Awareness, Swarm Shepherding, Transfer Entropy, Unmanned Aerial Vehicles

I. INTRODUCTION

The swarm shepherding problem has been researched in various contexts by many authors [1]. The problem has seen extensive use in different domains of applications including biological immune systems [2], horse harem groups [3], birds [4], and sheep [5], as well as ground [6] and aerial robotics [7], [8].

The prominent and most successful solution algorithms are biologically inspired ones. For example, Strömbom et al. [9] designed an algorithm that switches between two behaviours to herd the shoids successfully; collecting, and driving. A collecting behaviour occurs where the sheepdog positions itself behind the furthest sheep from the flock while facing the flock's Global Centre of Mass (GCM), defined as the Centre of Mass (CoM) of the flock [9]. A driving behaviour occurs where the sheepdog positions itself behind the flock while aligning its position on a ray emitting from its location towards the goal and passing through the flock's GCM. The resultant behaviour in a simulation environment was consistent with the behaviours observed in the real environment, where sheepdogs

herd sheep. Other push (repulsion) and pull (attraction), and influence-driven algorithms exist in the literature [10], [11].

The premise of the two behaviours adopted by Strömbom et al. are to maintain the sheep collected, even while driving the sheep towards the goal; hence, the GCM concept is vital. Strömbom et al. validated their model by contrasting the behaviours generated from the simulation against real data collected from Australian farms. However, the model assumed that the sheep are homogeneous point masses modelled using boids rules [12], as did Vaughan et al. [13] when modelling ducks.

We conducted over 50 field trials to herd a flock of Dorper sheep, *Ovis Aries* [14], using a UAV. In contrast to models such as those introduced by Strömbom et al., who assume that sheep are homogeneous, our field observations identified that the flock of sheep is far from being a homogeneous flock. In particular, we observed the existence of an influencing sheep that displays behavioural characteristics different from the rest of the flock.

The identification of the influencing sheep could improve the efficiency of the herding agent in collecting the sheep by aiming to herd the influencers with the remaining sheep expected to follow. This shifts the focus of the herding agent from the flock's CoM to what we call in this paper, the Centre of Influence (CoI). We demonstrate the potential of a CoI to offer a better rationale and a deeper understanding of the likely connectivity between the agents in the swarm. We hypothesise that the Centre of Influence within the swarm is where a shepherding agent should focus their influence in order to control a swarm, towards a goal optimally. By influencing the leaders in the herd, the herding agent could spend less time assigning its energy to tasks related to other sheep.

In the remainder of the paper, we begin by summarising relevant models of swarm shepherding, and how our proposed CoI concept differs from such models. We then present proposed new measures, experimental design, and results from applying these measures to a simulated swarm influence model. We conclude by detailing our future research work to use information from the CoI to control a swarm more efficiently.

II. MODELS OF SWARM SHEPHERDING

Strömbom et al. successfully demonstrate a generic two-rule switching algorithm that solves the single sheepdog shepherding problem [9] using the predator-prey relationship. Their model is based on empirical GPS data of an Australian sheepdog collecting and herding a flock of Merino sheep (*Ovis aries*). In this model, the underpinning sheep behaviours are based on the classic boids parameters of separation, cohesion, and alignment [12]. This models the sheepdog through two simple behaviours: collecting and driving. Strömbom et al. considered that the sheepdog sees *white fluffy things* in front of it and determines whether there are gaps between them. The sheepdog then determines whether these gaps are too large or increasing in size and reacts to promote a cohesive flock.

Similar to the reliance of the boids model on vector analysis, Strömbom et al. use force vectors to represent the interaction between the point masses representing the sheep and sheepdog. Initially, there are N shoids (which we designate as M1 shoids) randomly positioned within the bounds of the paddock. When the herding agent is released in the paddock, each shoid aims to remain close to its nearest neighbours ($\Omega_{\pi\pi}$) while maintaining a *safe* distance, $R_{\pi\beta}$, from the herding agent. If a shoid maintains a safe distance from the herding agent, it continues its randomised flocking behaviour. Shoid collisions are avoided by an inter-shoid repulsion force where the distance between shoids reduces below the repulsion distance threshold. Once the herding agent encroaches on a shoid's safe distance, a predation response is enabled. The shoid is subsequently attracted to the Local Centre of Mass (LCM) of its $\Omega_{\pi\pi}$ nearest neighbours, while also being repelled in the opposite direction to the herding agent. To better replicate natural behaviour, Strömbom et al. use weighting factors for each force, and stochastic effects by way of a weak inertia force and a small noise factor. The resultant linear combination of these weighted vectors, weak inertia, and noise, is the shoid's next position.

The herding agent's task is to *collect* all shoids present in the environment and *drive* the flock to a target location. To achieve this, we implement the herding agent per Strömbom et al.'s previously discussed biologically inspired switching algorithm. The herding agent behaves in one of two ways, B_1 and B_2 , which are dictated by the position of the shoids

B_1 : If all shoids are within a distance $f(N)$ of the flock's GCM, the herding agent aims to position itself directly behind the flock's GCM in relation to the target region, known as the *driving* position.

B_2 : If at least one shoid is further than $f(N)$ from the flock's GCM, a separated shoid, the herding agent aims to position itself directly behind the separated shoid in relation to the flock's GCM, known as the *collecting* position.

Additionally, if the herding agent assesses that it is too close to any of the shoids, it remains stationary for a period. This is due to an observation made during Strömbom et al.'s study that showed sheepdogs rarely approach flocks at close range

as it caused the flock to disperse rapidly (i.e. induces a *high* predation response).

The previous swarm control models share a common underlying fundamental assumption that the herding agent (be it a leader or a shepherd) calculates and determines its behaviour purely based on environmental spatial features. While valid for specific sizes of swarms [13], it is not always practical to calculate the required measures in applied settings due to sensor noise, missing or incomplete data feeds, or insufficient sensor fidelity or placement. Traditional measures also do not consider the natural swarm environmental, social or leader and follower hierarchies observed in our field trials, which significantly contribute to how the swarm reacts in different situations or to different external stimuli. We hypothesise they are not optimal to be the sole determinants of swarm control.

We have previously conducted field experiments on herds of six sheep [14], where we introduced a UAV as the herding agent, known as *Sky Shepherd*, to measure the response of the sheep. During the conduct of Sky Shepherd factor screening tests, the response of sheep was measured in terms of the sheep heart rate and distance from the Sky Shepherd. It was found sheep would permit the Sky Shepherd to drive at a closer range than a predator agent such as a sheepdog, with consistently lower heart rate than sheepdog or motorbike interactions. Predation risk occurs when a prey animal perceives a herding agent as a source of risk, in turn responding with behaviours (predation response) that promote self-preservation. In prey animals such as sheep, the collective predation response results in flocking behaviours, with the selfish herd behaviour widely accepted as the primary motive of prey response [15].

During flocking, some sheep exhibit centre-seeking behaviour [16], while other sheep will seek to lead the flock to safety [17]. Such leader-sheep display curiosity towards the herding agent, with a successful sheepdog, for example, using the greater jostling when driving the sheep towards the goal [18]. Different influencing behaviours were observed in the Sky Shepherd screening tests, which have been estimated with an initial variation of shoid parameters in our model. We iteratively vary these parameterisations in our heterogeneous agent simulation model. This assists in identifying influence measures to support herding algorithms.

III. LEADERSHIP IDENTIFICATION AND MEASURES OF INFLUENCE

We hypothesise that influencers will exhibit behavioural signatures that we may infer from their spatio-temporal information signatures; what we term as 'footprints' for ease of understanding that we mean 'where something is and where has it been'. We don't intend to make this investigation an inquiry into the internal logic of influence, but as an exploratory study to identify if the position information of a heterogeneous shoid swarm could carry information to identify footprints in a swarm. In practice, an observer only has access to the position of a swarm agent, without access to either the internal parameters or behavioural logic of the

agent. Therefore, our measures are derived from time-space-position information (TSPI). These measures seek to identify the presence of heterogeneous behaviours, forming the basis for a herding agent to identify areas where they may apply force to achieve the goal.

An *influence* is the set of information that causes an effect in the internal states, attitude or behaviour of a biological or artificial cognitive agent. For example, a sheepdog influences sheep due to the evolved sense of fear induced by the presence of the sheepdog within the sensor range of sheep. The CoI is inspired by the CoM presented in Strömbom et al.'s seminal work [9]. We define the CoI as the location of agents that if targeted to be influenced, the cascading of the influence on other agents will be maximum. Thus, CoI refers to an area or shoid that the herding agent could exert maximum influence on the flock with the least energy, at a point in time.

We derive our CoI portfolio of measures from the TSPI of the shoid and herding agents. The CoI consists of synchronicity (S), predation risk (PR), and situation awareness (SA). The reliance on spatial and information-theoretic measures to interpret swarm systems is an established area of research to infer higher-level behaviours and interactions within the swarm, with various examples in the literature [3], [19]–[22]. Our three indicators of synchronicity, predation risk, and situation awareness, have well-established foundations in the literature.

A. Synchronicity

We define *Synchronicity* as the alignment in time and space of action resulting from a significant influence. This definition is based on the work of Pikovsky et al. [23]. Our candidate measure for synchronicity is based on the information-theoretic measure of transfer entropy, which has been widely studied to understand the flow of information between agents within complex adaptive systems, such as swarms [20], [22], [24]. Transfer entropy is a non-parametric approach that provides a measure of the asymmetric, directed transfer of information between two stochastic processes [25]. Schreiber [26] first defined the transfer entropy as

$$T_{J \rightarrow I}(k, l) = \sum_{i,j} p(i_{t+1}, i_t^{(k)}, j_t^{(l)}) \cdot \log \left(\frac{p(i_{t+1} | i_t^{(k)}, j_t^{(l)})}{p(i_{t+1} | i_t^{(k)})} \right), \quad (1)$$

where $T_{J \rightarrow I}$ is a measure of information flow from agent J to I , where $p(\cdot)$ and $p(\cdot|\cdot)$ are the probabilities of historic states, k is the history length, and l is the lag. The essence of what transfer entropy is capturing here is the changing potential, which could be seen as the *surprise* of an outcome; we interpret this in our application as the change in the potential for divergence from current behaviour.

We select transfer entropy over other approaches due to the intuitiveness of its interpretation, and the well-established foundation of research use [20], [22], [24], [27], [28]. Our specific transfer entropy calculation methodology is based

on local transfer entropy [29] and implemented per [24], demonstrating the reconstruction of local information flows over time.

The local transfer entropy is a measure which characterises the spatial information transfer at each temporal point within a system. This provides insight to the dynamics of a system through time, a level of granularity that may otherwise be difficult to obtain [29], and which can be readily computed and thus potentially timely in the decision-making of shepherding tasks. Local transfer entropy has been used to classify swarming behaviours [24], as well as the role of influencers within swarms [30]. The local transfer entropy is defined as

$$te_{J \rightarrow I} = t(i, j, n + 1, l) = \lim_{k \rightarrow \infty} \log \frac{p(x_{i,n+1} | x_{i,n}^{(k)}, x_{i-j,n}^{(l)})}{p(x_{i,n+1} | x_{i,n}^{(k)})}. \quad (2)$$

We assume our analysis is of a first-order Markov process and therefore set the embedding dimension (k), embedding delay (τ) and lag (l) equal, such that $k = \tau = l = 1$ [25], [29]. Under this first degree Markovian assumption, we implement Equation 2 per [24] as

$$te_{J \rightarrow I} = t(i, j, n) = \log \frac{p(x_{i,n} | x_{i,n-1}, x_{i-j,n-1})}{p(x_{i,n} | x_{i,n-1})}. \quad (3)$$

Our evaluation quantities of interest are based on the local transfer entropy, per Equation 3. We identify two summary measures being the Net Transfer Entropy (NetTE) and the Total Transfer Entropy (TotTE), defined in [22]. We define NetTE here as

$$T_{J \rightarrow I}^{\text{net}} = \text{NetTE}_{J \rightarrow I} = te_{J \rightarrow I} - te_{I \rightarrow J}. \quad (4)$$

The NetTE has been used in previous studies to inform about the dynamics of a swarm, such as [22], [31], [32]. If non-zero, the NetTE provides insight as to the asymmetry for a pairwise interaction. In Equation 4, if the result is positive then we can infer that J is informative, or influences, I . If the result is negative, then we can infer that J is misinformative, or is influenced by, I . For cases where the result is zero, we may infer either that there is no coupling between J and I , or that the interaction is symmetric. Within this paper, we use the NetTE measure to quantify the symmetry, or asymmetry, of pairwise interactions.

We define TotTE here as

$$T_{J \rightarrow I}^{\text{tot}} = \text{TotTE}_{J \rightarrow I} = te_{J \rightarrow I} + te_{I \rightarrow J}. \quad (5)$$

The TotTE measures the magnitude of total influence for a pairwise interaction. This differs to the NetTE as it does not consider directionality, providing no information as to the level of symmetry or asymmetry. Equation 5 captures the size of a pairwise interaction, without attribution for “how much” J or I contribute. Within this paper, we use the TotTE measure to quantify the intensity of pairwise interactions.

We combine Equation 4 and Equation 5 as our summary measure for synchronicity, defined as

$$S_{J \rightarrow I}^t = \text{sgn}(T_{J \rightarrow I}^{\text{net}}) * |T_{J \rightarrow I}^{\text{tot}}|. \quad (6)$$

where $sgn(\cdot)$ returns the direction of the interaction from the $NetTE_{J \rightarrow I}$ quantity. We characterise three key cases from the perspective of the source agent (J) to the target agent (I), being:

- C_1 : $S_{J \rightarrow I} > 0$. J is informative, or influences, I . This case represents the synchronous leadership of J towards I .
- C_2 : $S_{J \rightarrow I} < 0$. J is misinformative, or is influenced by, I . This case represents the synchronous followership of J towards I .
- C_3 : $S_{J \rightarrow I} = 0$. J does not inform, or does not influence, I . This case represents asynchronicity.

For the cases when $S_{J \rightarrow I} \gg 0$ or $S_{J \rightarrow I} \ll 0$, we assert that this indicates the intensity of the relationship between J and I .

We are able to measure synchronicity between any two agents in the system, be it herding agent-to-shoid ($\beta \rightarrow \pi_i$), shoid-to-shoid ($\pi_i \rightarrow \pi_j$), or GCM-to-shoid ($\Gamma_{\Pi} \rightarrow \pi_i$). To explore intra-swarm dynamics, we consider the GCM as an information source within our analysis. We implement the GCM as the uniformly-weighted, average position at each time period for all shoids ($\Pi = \{\pi_1 \dots \pi_N\}$), given as $\Gamma_{\Pi} = \frac{1}{|\Pi|} \sum_i^{\Pi} P_{\pi_i}$. Similar to Strömbom et al., we assume shoids have an attraction to the GCM, affording an informative perspective to understand the dynamics of swarm collective behaviour.

B. Predation risk

We define *Predation Risk* (PR), based on the work of Lima and Dill [33], as the likelihood of an agent encountering a predator and the potential to safety, should this predator (perceived or real) attack the same agent. We state that a shoid exhibiting leader-like behaviours will attempt to assess herding agent actions, therefore increasing its predation risk, relative to its ideal position in the flock. As detailed by Morrell et al. [34], shoids are more successful at preventing attack by flocking to close neighbours first and joining the main flock as the attack continues. This strategy has been successful in simulation and associated with vervet monkey's (*Cercopithecus aethiops*) predation response to evade leopards (*Panthera pardus*), and guppy fish (*Poecilia reticulata*) strategy to evade diverse predatory types. Figure 1 depicts such a situation where the herding agent seeks to shepherd the shoids towards a defined goal location.

The bin-order (O_b) characterises the relative position and configuration of the swarm agent to that of the shepherd. We calculate the number of bins (B) as the ceiling-integer for the square root value of the number of sheep in the flock, such that $B = \lceil \sqrt{N} \rceil$, where N is the ceiling cardinality of Π . Bins are uniformly distributed from the closest agent to the shepherd to the furthest, assigning a bin-order number from 1 (closest) to B (furthest), as depicted in Figure 1. Our model assumes that the position O_1 has the highest PR, and the position $O_{\Gamma_{\Pi}}$ has the lowest PR.

While a herding agent exhibiting behaviour B_1 or B_2 may not exhibit a predatory attack behaviour, the flocking to nearest neighbours first supports the flock in responding to the

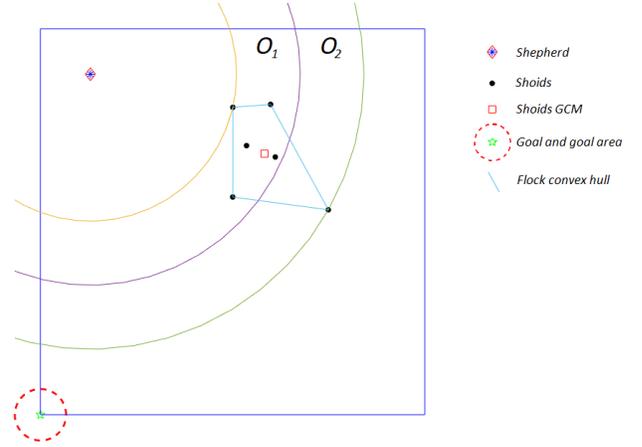


Fig. 1: Agent-based herding model based on [9], with modified shoid agents.

perceived predation risk of the herding agent. We suggest that during the shepherding task, a shoid seeking to gain awareness over promoting survival will seek a position in a region closest to the shepherd (O_1). In contrast, other shoids will seek a position nearer to the GCM of the flock ($O_{\Gamma_{\Pi}}$). Given the predation response to seek nearest neighbours, if a shoid is in the region O_1 , the highest PR will occur when there are no neighbours ($\Omega_{\pi\pi} = 0$), while lowest PR will occur when a shoid is in the GCM of the flock, with maximum nearest neighbours ($\Omega_{\pi\pi} = N - 1$). We calculate PR as

$$PR_{\pi_i}^t = \frac{1}{O_b} * \frac{N}{\Omega_{\pi\pi} + 1}. \quad (7)$$

Therefore, the shoid π_i at time t , within region O_1 , with no neighbours ($\Omega_{\pi\pi} = 0$), and within the interaction radius ($R_{\pi\pi}$) will have a higher PR than the shoid π_j at time t , within region O_b , when $b > 1$ and/or $\Omega_{\pi\pi} > 0$.

C. Situation awareness

Situation awareness (SA) is a well-defined concept in many domains, modelled here as a combination of both information-theoretic and spatial measures. We use the definition of Endsley [35] and define *Situation Awareness* as the perception of the elements in the environment within a volume of time and space (level 1 SA), the comprehension of their meaning (level 2 SA), and the projection of their status soon (level 3 SA) [35]. Within this model, we simulate an agent who positions itself to promote its ability to project (reach higher SA).

We hypothesise that a natural tension exists between the PR and SA of a shoid, which manifests with candidate influencers trading-off between high SA and low PR. In our model, SA is maximised when there exists an unobstructed line-of-sight between a shoid and the herding agent and is minimum at the furthest point of the convex hull from the herding agent with the greatest number of line-of-sight obstructions. We calculate the SA through the spatial measures of distance to the herding agent, distance to the GCM (Γ_{Π}) and the number of shoids

impeding the line-of-sight for each shoid and the herding agent. We denote the number of line-of-sight impediments as Θ , and distance as d from $\pi_i \rightarrow \beta \forall \pi_i \in \Pi$. We calculate the SA as:

$$SA_{\pi_i}^t = \frac{1}{\frac{d_{\pi_i \rightarrow \beta}^2}{d_{\pi_i \rightarrow \Gamma_{\Pi}} * d_{\Pi \rightarrow \beta}} * \Theta + 1}. \quad (8)$$

We hypothesise this combination of measures will detect an influencer shoid's attempt to obtain greater SA. By placing itself in a position close the convex hull boundary of the swarm, and therefore closer to the herding agent, it is likely to distance itself further from the GCM to perceive the elements in its environment (level 1 SA). The general location of this position exposes the shoid to the herding agent, and therefore allows it to obtain a higher level of information on the status of the current situation. It thereby allows the influencer to fully comprehend the situation (level 2 SA) before attempting to predict the future state (level 3 SA) of the herding agent.

IV. EXPERIMENTAL DESIGN AND ANALYSIS

A. Experimental Design

In this study, we seek to understand how our candidate measures of synchronicity, predation risk and situation awareness detect aggregate flock behaviours and describe the dynamics and associated influence of a homogeneous or heterogeneous simulated herd. This is modelled through the use of two distinct behaviours described in Table I, being a classic shoid (M1) [9] and a parameterised shoid (M2). To represent divergent behaviours, we have applied the weightings displayed in Table I. We assume that the shepherd knows the positions of every agent within the environment and the goal location. Whereas, the shoids are unaware of agents outside their sensing zone, and is unaware of the goal location. The simulation experiment is void of sensor and actuator noise; we acknowledge these are essential factors to consider [36] for real-world experiments [14].

Parameter changes for shoid M2 from those described in Strömbom et al. (shoid M1) were made to approximately reflect observed characteristic differences in [14]. The value representing shoid-shoid repulsion ($W_{\pi\pi}$) has been increased; therefore, the weight of repulsion from other shoids is high, simulating curiosity for shoid M2. The value representing shoid attraction to LCM ($W_{\pi s\Lambda}$) has been decreased to reflect shoid M2's role in internally influencing other flock shoids. The value of shoid predation risk ($W_{\pi s\beta}$) has been increased as shoid M2 has a higher propensity to be further away from the flock to observe the herding agent, which also manifests as an increased repulsion from the herding agent. Parameter changes to represent shoid M2 behaviour are based upon the algorithm represented in Figure 2.

We demonstrate our candidate measures through an attraction-repulsion swarm shepherding model, based on Strömbom et al. [9]. Shoids M1 are parameterised such that $W_{\pi\pi} > W_{\pi\Lambda} > W_{\pi\beta}$, while shoids M2 are parameterised such that $W_{\pi\pi} > W_{\pi\beta} > W_{\pi\Lambda}$. We analyse the impact of

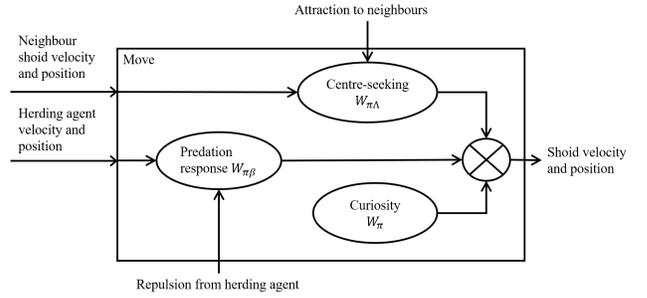


Fig. 2: Shoid agent algorithm to simulate flock movement during herding.

changing the configuration makeup of the flock for a constant simulation seed. Our simulations investigate the performance of our measures for six (total) shoids and one sheepdog, with the shoids varying between 0 and 6 for each agent type. The selection for the number of shoids was to ensure consistency with previously conducted live experimentation. We compare the insights derived from these simulation trials to those from our live experimentation data.

This section intends to characterise flock-level processes and behaviours as the first step to validate our measures, which must be completed before online analysis or use to identify internal flock social hierarchies and leadership dynamics. We reveal that we can recreate the qualitative narrative of interaction, without observation of the underlying agent interaction.

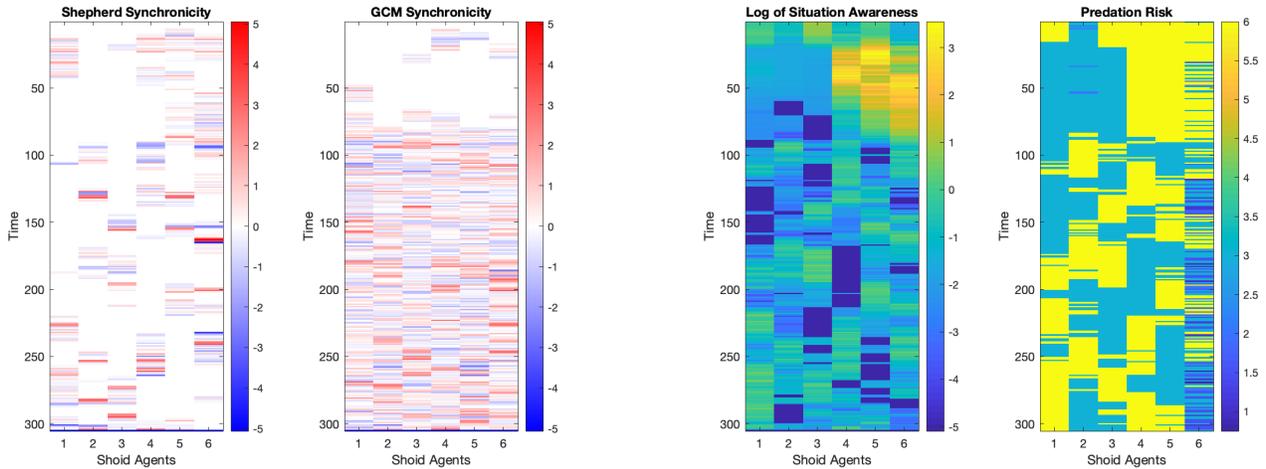
B. Simulation Results

Figure 3a depicts our synchronicity measure from the perspective of the shepherd (left) or GCM (right) as the source agent (J), to each shoid within the system. The visualisation of synchronicity corresponds to the cases outlined in Section III-A, with a consistent colour palette per [24]. The colour red represents C_1 , the colour blue represents C_2 , and C_3 is white. Colour intensity represents interaction magnitude.

We observe two main periods of change at the system level, being the initial phase where the shepherd is collecting the shoids, and the subsequent driving phase which dominates the remainder of the simulation. There is insufficient evidence ($H(5) = 18.9, p < 0.1$) to suggest that there is a significant difference between the synchronicity of shoids across the measurement between the shepherd and GCM within our simulation trials. There is also insufficient evidence to suggest that there is a significant difference between the synchronicity across shoids within each shepherd and GCM synchronicity measure. We conjecture that the presence of a statistically significant synchronicity result may contribute to defining a social hierarchy of leadership. Where no statistically significant result exists, we suggest that there is presently no identifiable leader shoid. Our simulated results represent a plausible instance of the observed field trial behaviours. The developed CoI portfolio allows us to identify variance in behaviour between shoids of a swarm, allowing us to characterise the contribution of individual shoids.

TABLE I: Agent parameterisation for the simulated swarm shepherding model environment.

Description	Classic shoid (M1)	Parameterised shoid (M2)	Herding Agent
Shoid-shoid Repulsion Radius ($R_{\pi\pi}$)	2	3	
Shepherd detection distance ($R_{\pi\beta}$)	30	30	30
Shoid-shoid Repulsion weight ($W_{\pi\pi}$)	2	3	
Shoid attraction to LCM ($W_{\pi\Lambda}$)	1.05	0.5	
Shoid Predation Risk weight ($W_{\pi\beta}$)	1	1.5	
Speed (S)	1	1	1.5



(a) Synchronicity for the Shepherd (left) and Flock GCM (right), where J is the agent of interest and I is each shoid. (b) Summary of Situation Awareness (left) and Predation Risk (right) for each shoid.

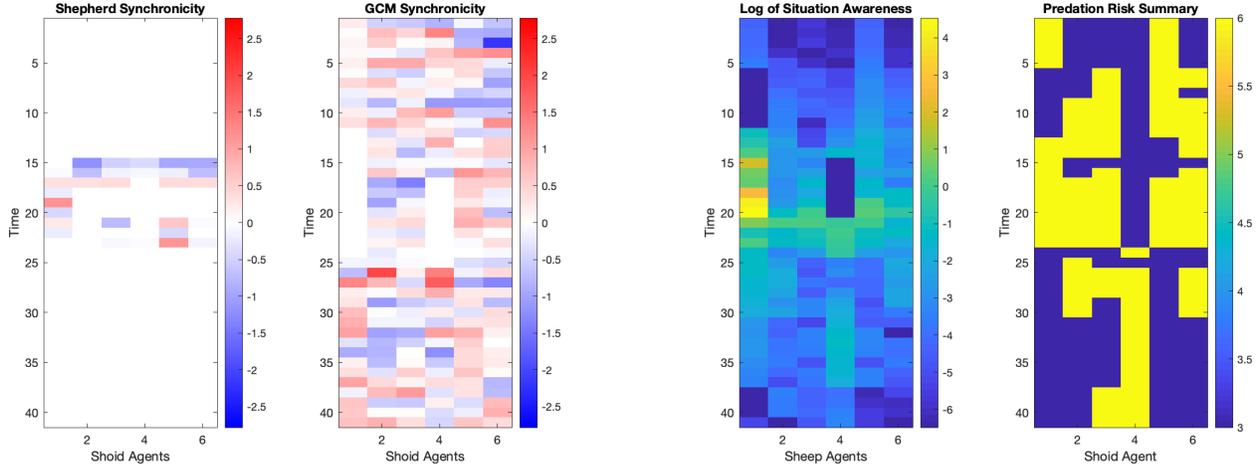
Fig. 3: Summary measures for simulated data over $t = 300$ time steps.

The variation between the synchronicity of shoids is observed in Figure 3a. We observe that during the collecting phase of the simulation that there is an increase of synchronous contact with the shepherd, which corresponds to a reduction in synchronous contact with the GCM. The external source present *competes* with the internal dynamics of the flock for control and influence, reducing the level of synchronicity for a discrete period. This is shown by an increase of synchronicity with the shepherd (Cases C_1 and C_2), corresponding to a reduction in synchronicity, representative of asynchronicity, with the GCM (Case C_3). The key insight here is that the active influence of the shepherd reduces the effectiveness of the shoids attraction to the GCM, forcing a change in the configuration state of the flock. Throughout the phases following, a more consistent profile of synchronicity is observed with both the shepherd and GCM. This potentially indicates configuration stability within the internal dynamics of the flock, such that a steady-state has been achieved.

The granularity of the PR measure is susceptible to flock size (N), requiring care to interpret if void of synchronicity or SA. The results in Figure 3b reveal shoid 6 as the only shoid seeking to lower their PR throughout, reflected by the continual variation of PR values. It can be inferred that shoid 6 has a higher attraction to the LCM $W_{\pi\Lambda}^6 > W_{\pi\Lambda}^i$ where $i = \{1, \dots, 5\}$. A statistically significant difference ($H(5) = 117.87$, $p < 0.001$) exists between the predation risk of shoid agents within the Figure 3b.

There exists a distinct period of high SA within the initial herding agent contact, and collection of the shoids. SA can characterise the flock configuration change, representing a heightened awareness during this change. This is evident throughout the initial and collecting phase, revealing shoids 4–6 are closer to the shepherding agent, which normalises during the subsequent driving phase. Note that we depict a transformation of SA, $\log(SA)$, for ease of readability in all SA figures presented. A statistically significant difference ($H(5) = 157.16$, $p < 0.001$) exists between the situation awareness of shoid agents within the Figure 3b, allowing for identifying of differences between each shoid.

Considering measures across S , PR , and SA , we can identify further features of the flock. From approximately time-step 200, we see a jostling between shoid 1 and shoid 2 that is indicative ideally of behaviour to promote their SA. This is also reflected with lower synchronicity with the GCM. Also reflected are periods when a shoid is responding more to the herding agent, with higher PR and greater jostling within the flock to project SA. As discussed in Section III, our portfolio of measures are designed to detect the evolutionary dynamics in the flock. The typical story they tell is one of the changes in the system, such as the internal state of configuration or principal-agent of influence, or control.



(a) Synchronicity for the Shepherd (left) and Flock GCM (right), where J is the agent of interest and I is each shoid. (b) Summary of Situation Awareness (left) and Predation Risk (right) for each shoid.

Fig. 4: Summary measures over a discrete period of contact ($t = 40$) for live experiment data.

C. Sky Shepherding Field Data Results

Contrasting the simulated data to live experimental data using real sheep, we can characterise when the Sky Shepherd asserts dominance in the system over any of the sheep in the flock. Notably, we have identified that the flock experiences change through our measures, not stabilising until after contact with the Sky Shepherd. The researcher’s observational notes reveal that this is representative of the system as the flock remained disjoint through to the end of this trial (which was ended due to high sheep heart rate), as per University of New South Wales Animal Ethics Committee approval 19/122B. Figure 4 shows 40 seconds of interaction between a flock of 6 sheep and the Sky Shepherd. This time slice has been selected to depict the interaction of the Sky Shepherd with the flock and the associated response to this external stimulus.

A statistically significant difference ($H(5) = 20.18$, $p < 0.05$) exists between the synchronicity of sheep across both shepherd and GCM measures within our experimental trials, Figure 4a. There is a lack of evidence to suggest that there is a significant difference between the synchronicity across sheep within each shepherd and GCM synchronicity measure. This indicates our flock is acting with a tacit goal, such as preserving the safety of the flock members.

A statistically significant difference ($H(5) = 36.1$, $p < 0.001$) exists between the predation risk of sheep within our experimental trials, Figure 4b. The response of Sheep 4 during the Sky Shepherd field trials indicates she was the last to respond to the Sky Shepherd and flock influence, which is reflected by a sudden and sustained change in PR, minimal reaction to the Sky Shepherd and lower interaction with GCM. We also observe that the PR increases during periods of flock configuration change, returning to a relative baseline after these periods.

A statistically significant difference ($H(5) = 183.1$, $p <$

0.001) exists between the situation awareness of sheep within our experimental trials, Figure 4b. We identify Sheep 1 as the influencer within the flock, with her longer synchronicity with the Sky Shepherd, and highest SA, identifying her as the first to respond. The influence of Sheep 1 within the flock is also reflected in a change of synchronicity with the GCM in Figure 4a, as she influences the flock to move away from the Sky Shepherd. Sheep 5 is the first to follow her, with Sheep 4 trailing behind. We observe that the mean SA increases under external influence, returning to a baseline level over a longer period when compared to the period of increase.

V. CONCLUSION

We have proposed a portfolio of measures that indicate the CoI to identify impacts on flock dynamics. The proposed three measures reveal footprints within a swarm with rich information to reveal the most influential agent in the herd. The selected candidate measures have successfully described the nonlinear dynamics of a simulated swarm, initially illustrating the approach with shoids; based on the M2 model developed, the designed metrics assist with identifying agents with influence in the flock, thereby verifying the prospect of the proposed new metrics. Our biologically inspired model comes from observing the interaction of a shepherd and flock of sheep.

Using our developed CoI metrics, we have been able to identify influencer sheep within collected experimental data from biological agents. Future work will need to enable classification of types of influence within the flock to support developing greater efficiency in shepherding algorithms, thereby supporting the development of artificial intelligence when compared to classical approaches [37]. This will provide an opportunity to refine the proposed model and include further granularity in subordinate measures, such as head

position and body orientation, relative to the position of the shepherding agent.

There are many domains of application for this research, both biological and artificial, for control and other purposes. The CoI approach may aid in discovering new methods to understand dynamic hierarchies, as well the influence of external agents to a system—allowing us to develop robust artificial intelligence, capable of understanding the variance that exists in biological models.

Our preliminary experimentation with both simulated and live data indicates that our measures can successfully describe the aggregate flock system properties and identify disparate influences through a comparative analysis. However, what we cannot characterise yet is the individual contribution of each agent in the system and classify these behaviours to infer the constituent agent makeup and infer social hierarchies. Additionally, a more in-depth sensitivity analysis will include a longitudinal analysis to describe the effect of parameter variation between agents in the system, as well as further investigate the performance of our measures on live experimental data.

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