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 to model predation risk in predator-prey dynamic. Previous work assumed homogeneous shoids. Real-world observations on 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 shoid with different parameters from the remainder of 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 actual sheep herding trial by an Unmanned Aerial Vehicle (UAV) to validate the proposed measures. The resultant footprints will allow us in our future research to design more efficient control strategies for the UAV to improve the herding of sheep, by polarising the attention of the machine learning algorithm on those Shoids with influence footprints to drive the flock.**

***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], 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 sheep successfully. The resultant behaviour in a simulation environment was consistent with the behaviours observed in the real environment, where sheepdogs herd sheep. Other push and pull, and influence-driven algorithms exist in the literature [10], [11].

Strömbom et al. 's [9] algorithm switches between two behaviours; 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. 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 global centre of mass (GCM).

The premise of both behaviours is to maintain the sheep collected, even while driving the sheep towards the goal; hence, the global centre of mass concept is vital. Strömbom et al. validated their model by contrasting the behaviors 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]. Vaughan et al. [13] also assume that flocks are homogeneous 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 centre of mass (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 $\Omega_{\pi\pi}$ nearest neighbours while maintaining a *safe* distance 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 predation risk boundary, 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, resulting in the shoid's next position.

The task of the herding agent is to *collect* all shoids present in the environment and *drive* them 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, which are dictated by the position of the shoid.

- Behaviour one: if all shoids are located 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.
- Behaviour two: if at least one shoid is further than $f(N)$ from the flock's GCM, known as 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 dog, with consistently lower heart rate than dog 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].

While sheep do exhibit flocking, where some sheep exhibit centre-seeking behaviour [16], 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, with the first iteration of variation in parameterisation implemented in our heterogeneous agent simulation model to assist with 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 spatiotemporal 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 into an inquiry into the psychology of influence, but as an exploratory study to identify if the position information of a heterogenous 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 all derived from time-space-position information (TSPI). These measures to identify the presence of heterogeneous behaviours form the basis for a herding agent to use to identify areas to apply energy in order to achieve the goal.

We group the CoI measures (see Equation 1) into three indicators: synchronicity (S), predation risk (PR), and situation awareness (SA). We begin by providing working definitions for the essential elements of each indicator.

$$CoI = f(S; PR; SA) \tag{1}$$

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 fear induced by the presence of the sheepdog within the sensor range of sheep. The *Centre of Influence (CoI)* is inspired by the CoM presented in Strömbom at al.'s seminal work [9]. We define the CoI as the location of agents which if targeted to be influenced, the cascading of the influence on other agents will be maximum. Thus, CoI refers to an area that the herding agent could exert maximum influence on the flock with the least energy.

The three indicators for CoI are all driven from TSPI of the shoid and herding agent. 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, which we use in our novel concept of CoI.

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 transfer entropy measure, 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 it as

$$T_{J\to I}(k,l) = \sum_{i,j} p\left(i_{t+1}, i_t^{(k)}, j_t^{(l)}\right) \cdot log\left(\frac{p\left(i_{t+1}|i_t^{(k)}, j_t^{(l)}\right)}{p\left(i_{t+1}|i_t^{(k)}\right)}\right), \tag{2}$$

where $T_{J\to I}$ is a measure of information flow from agent J to I, and $T_{J\to I}$ is a measure of information flow from agent I to J, where $p(\cdot)$ and $p(\cdot|\cdot)$ are the conditional 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] which can be readily computed and thus potentially timely in the decision-making of shepherding. 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

$$t(i,j,n+1,l) = \lim_{k\to\infty} \log \frac{p(x_{i,n+1}|x_{i,n}^{(k)}, x_{i-j,n}^{(l)})}{p(x_{i,n+1}|x_{i,n}^{(k)})}. \tag{3}$$

As our analysis is of first-order Markov process, we set the embedding dimension, embedding delay and lag equal, such that $k = \tau = l = 1$ [24], [25], [29].

Our evaluation of the local transfer entropy within the system is based on two summary measures, being the Net Transfer Entropy (NetTE) and the Total Transfer Entropy (TotTE). The NetTE is defined as

$$T_{J\to I}^{\text{net}} = \text{NetTE}_{J\to I} = \text{TE}_{J\to I} - \text{TE}_{J\to I}, \tag{4}$$

which is detailed in [22]. We use the NetTE to inform the information flow dynamics of the internal swarm. Specifically, we seek to quantify emergent local structures and heterogeneous agent hierarchies, which may offer insights to internal swarm influence.

To explore intra-swarm dynamics, we consider a GCM as the information source within our analysis for the NetTE measure. 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 $\Gamma_\Pi = \frac{1}{|\Pi|}\sum_i^{\Pi} P_{\pi_i}$. The implementation assumes, similar to Strömbom et al., that shoids have an attraction to the CoM, affording an informative perspective to understand the dynamics of swarm collective behaviour.

The TotTE is defined as

$$T_{J\to I}^{\text{tot}} = \text{TotTE}_{J\to I} = \text{TE}_{J\to I} + \text{TE}_{J\to I}, \tag{5}$$

as described in [22]. The TotTE is used to measure the overall degree of mutual influence between two agents (herding agent-shoids ($\beta \to \pi_i$), shoid-shoid ($\pi_i \to \pi_j$), or GCM-shoid ($\Gamma_\Pi \to \pi_i$)), establishing the magnitude of pairwise information dynamics. We use the TotTE to capture the intensity of the pairwise interaction for each pair.

Our summary measure for synchronicity is a combination of both the NetTE and the TotTE, which we define as

$$S = \text{sgn}\left(T_{J\to I}^{\text{net}}\right) * |T_{J\to I}^{\text{tot}}|. \tag{6}$$

We characterise two important cases from the perspective of the source, being

- $+$ information flow and high magnitude, as the source agent informing on the future state of the target agent (synchronicity); and
- $-$ information flow and high magnitude, as the source agent not informing on the future state of the target agent, but who remains in contact with the swarm (asynchronicity).

B. Predation risk

We define predation risk (PR), based on the work of Lima and Dill [31], 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. [32], flocking agents are more successful at preventing attack by flocking to close neighbours first and joining the central 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.

We assume that in (Fig 2)

- The position O_1 has the highest PR.
- The position O_{Γ_Π} has the lowest PR.

Where 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 integer square root value of the number of sheep in the flock, such that $B = \sqrt{N}$, where N is the 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 2.

While a herding agent exhibiting behaviours of collect and drive may not exhibit a predatory attack behaviour, the flocking to nearest neighbours first supports the flock in responding to the perceived predation risk of the herding agent. We state that while all shoids will seek nearest neighbours during the shepherding task, a shoid seeking to gain awareness over promoting survival will position itself in a region closest to the shepherd (O_1). In contrast, other shoids will seek to position itself in the GCM of the flock (O_{Γ_Π}). 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 ($\Omega_{\pi\pi} = 0$).

We calculate PR based on two features, being

- Order from the herding agent, O_b, where $b \in \{1, \ldots, B\}$, such that the convex hull area of the flock is divided in B uniform spaces, with $O_{\Gamma_P i}$ at the centroid.
- $\Omega_{\pi\pi}$, where $\Lambda_\pi \in \{0, \ldots, N-1\}$, such that $N-1$ is the maximum nearest neighbours possible within the shoid's interaction distance ($R_{\pi\pi}$).

where $PR^t_{\pi_i}$ is bounded by $[0, \Pi]$. Consequently, we calculate PR as

$$PR^t_{\pi_i} = \frac{1}{O_b} * \frac{N}{\Omega_{\pi\pi} + 1} \tag{7}$$

Therefore, shoid π_i at time t, within region O_1, and with no neighbours, $\Omega_{\pi\pi} = 0$, within the interaction radius $R_{\pi\pi}$, has a higher PR than 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 [33] and define *Situation Awareness* as the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status soon [33]. Within this model, we simulate an agent who positions itself in order to promote its ability to project (reach higher SA).

We assume that a natural tension exists between the PR and SA of an agent, which manifests with candidate influencers trading-off between high SA and low PR. In our model, SA is maximum when there is a clear 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 highest number of line-of-sight impairments. We calculate the SA through the spatial measures of distance to the herding agent, distance to the GCM ($\Gamma_P i$) and the number of shoids impeding the line-of-sight between shoid$_i$ and the herding agent. We denote the number of line-of-sight impediments as Θ, and distance as d from $x \rightarrow y$. We calculate the SA as:

$$SA^t_{\pi_i} = \frac{1}{\frac{d^2_{\pi_i \rightarrow \beta}}{d_{\pi_i \rightarrow \Gamma_\Pi} * \ d_{\Pi \rightarrow \beta}} * \Theta + 1}, \tag{8}$$

such that SA_{π_i} is bounded in $(0, L^2]$, where L is the paddock size and the $d_{\Pi \rightarrow \beta} \geq 1$.

We hypothesise this combination of measures will detect an influencer shoid's attempt to gain higher 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 per Table I, being a classic shoid (M1) [9] and a parameterised shoid (M2). To represent divergent behaviours, we have applied weightings displayed in Table I.

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

Parameter changes from those described in Strömbom et al. were made to approximately reflect observed characteristic differences in [14]. The value $W_{\pi\pi}$ has been increased; therefore, the weight of repulsion from other shoids is high, simulating shoid M2 curiosity. The value of $W_{\pi s\Lambda}$ has been decreased to reflect the role of the shoid M2 in internally influencing flock shoids. The value of $W_{\pi s\beta}$ has been increased as shoid M2 has a higher propensity to be further away from the flock to observe the herding agent. This also manifests as a stronger repulsion from the herding agent. Parameter changes to represent shoid M2 behaviour are based upon the algorithm represented in Figure 1.

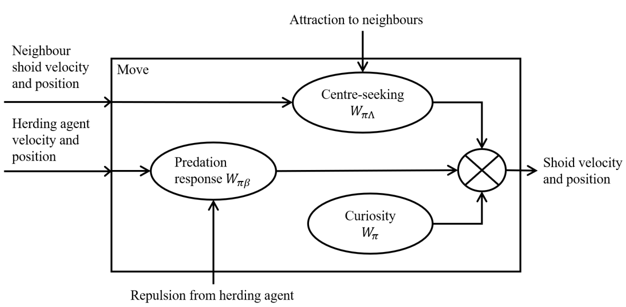

Fig. 1. Shoid agent algorithm to simulate flock movement during herding.

Shoid M2 is parameterised with $W_{\pi s\Lambda} > W_{\pi a\Lambda}$ to represent a surprise behaviour, or influence to move the flock based on the presence of the herding agent. Consequently, the predation response is represented as $W_{\pi s\beta} > W_{\pi a\beta}$. To represent curiosity of the shoid leader, the weight of repel from neighbours is $W_{\pi s} > W_{\pi a}$. Overall, the parameterisation of shoids holds the conditions of [9], whereby $W_{\pi s} > W_{\pi s\Lambda} > W_{\pi s\beta}$ and for follower shoids, $W_{\pi a} > W_{\pi a\Lambda} > W_{\pi a\beta}$.

We demonstrate our candidate measures through an attraction-repulsion swarm shepherding model, based on Strömbom et al. [9], with the introduction of our shoids as per Table I. Key spatial and agent features of the system are visually interpreted, such as

- Herding agent, denoted by the red diamond.
- Shoids, denoted by black dots (note that the candidate leader shoid has not been differentiated).
- Shepherd goal, denoted by the red circle at the $(0, 0)$ (bottom left) origin.
- GCM, denoted by the red square within the flock.
- Discrete bins, denoted by the concentric circles radiating outward from the shepherd.
- Convex hull of the flock, denoted by the red line connecting the outer-most shoids of the flock.
- Movement boundary, denoted by the enclosed blue box.

We analyse the impact of 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 live experimentation, previously conducted. We compare the insights derived from these simulation trials to those from our live experimentation data.

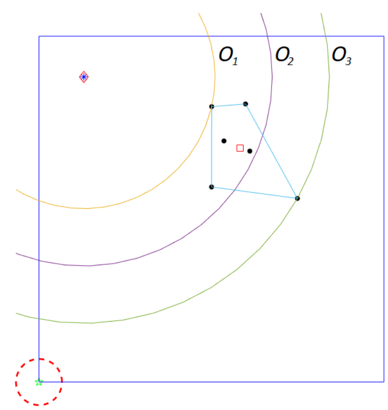

Fig. 2. Agent-based herding model based on [9], with modified shoid agents.

B. Results

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.

C. Simulation Results

Figure 3 depicts our synchronicity measure from the perspective of the shepherd as the source agent (left) and GCM as the source agent (right), to all shoids within the system. 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 both shepherd and GCM measures within our simulation trials, per Figure 3. 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.

Upon further inspection of Figure 3, variation between the synchronicity of shoids is evident. We observe that during the collecting phase of the simulation that there is an apparent 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. Throughout the driving phase, a more consistent profile of synchronicity appears, potentially indicating stability within the dynamic of the flock, that a steady-state has been achieved.

The granularity of PR is susceptible to flock size (N), translating to care required when interpreting PR without the support of synchronicity or SA. However, the results in Figure 3 reveal a split flock initial state, with shoids 1, 2 and 3, further from the herding agent. At approximately time step 100, a single flock is formed, with only shoid 6 seeking to lower their PR throughout. Shoid 6 centre-seeking behaviour is reflected with the continual variation of PR values, and minimal instances of high PR. It can be inferred that shoid 6 has a higher attraction to the LCM $W^{6}_{\pi\Lambda} > W^{i}_{\pi\lambda}$ where $i = \{1, 2, 3, 4, 5\}$. A statistically significant difference ($H(5) = 117.87$, $p < 0.001$) exists between the predation risk of shoid agents within the Figure 3.

Figure 3 shows a distinct period of high SA within the initial herding agent contact, and collection of the shoids 4–6. SA can characterise the flock configuration change, representing a heightened awareness during this change. This is evident throughout the initial and collecting phase of the simulation. It reveals that agent 4–6 are closer to the shepherding agent, with relatively few other agents blocking their line-of-sight to the shepherding agent. This normalises during the driving phase to a relative baseline level. Note that we depict a transformation of SA, $log(SA)$, for ease of readability in the figure. A statistically significant difference ($H(5) = 157.16$, $p < 0.001$) exists between the situation awareness of shoid agents within the Figure 3, allowing for identifying of differences between each shoid.

Considering measures across synchronicity, PR, and SA, we can identify further features within the flock. Despite the split flock, shoid 1 responds the most to the movement of the herding agent, which is reflected during the first 50 time steps of Shepherd Synchronicity pictured in Figure 3. There is evidence of jostling to promote SA for shoid 1 during the same period in Figure 3. Once the flock merges, at approximately 100-time steps, we see the regular responses from shoid 6 to the GCM in Figure 3, which is also reflected in the lower overall PR in Figure 3. From approximately time-step 200, we see a jostling between shoid 1 and shoid 2 to promote their SA. This is also reflected with lower synchronicity with the GCM. Also reflected in Figure 3, we see periods when a shoid is responding more to the herding agent, with higher PR and greater jostling within the flock to project SA. As we discuss in Section III, our measures are designed to detect distinct dynamics of the flock. The typical story they tell is one of significant changes in the system, such as the internal state of configuration or principal-agent of control.

D. Historic 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 becomes quite unstable through our measures and does not stabilise 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 HR), as per University of New South Wales Animal Ethics Committee approval (ACEC 19/122B).

Figure 4 depict 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, per Fig 4. 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, per Figure 4. 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 the sudden and sustained change in PR, minimal reaction to the Sky Shepherd and lower interaction with GCM in Fig 4. 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, per Figure 4. 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. Sheep 1 influence within the flock is also reflected in the lack of synchronicity with the GCM in Figure 4, 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

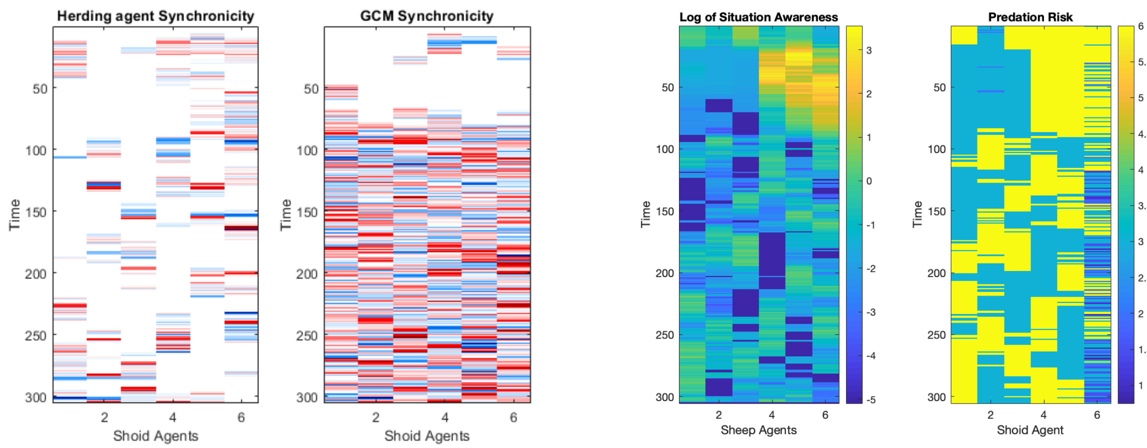

Fig. 3. Synchronicity summary measures (on left) and Predation Risk and Situation Awareness summary measures (on right) for the simulated data.

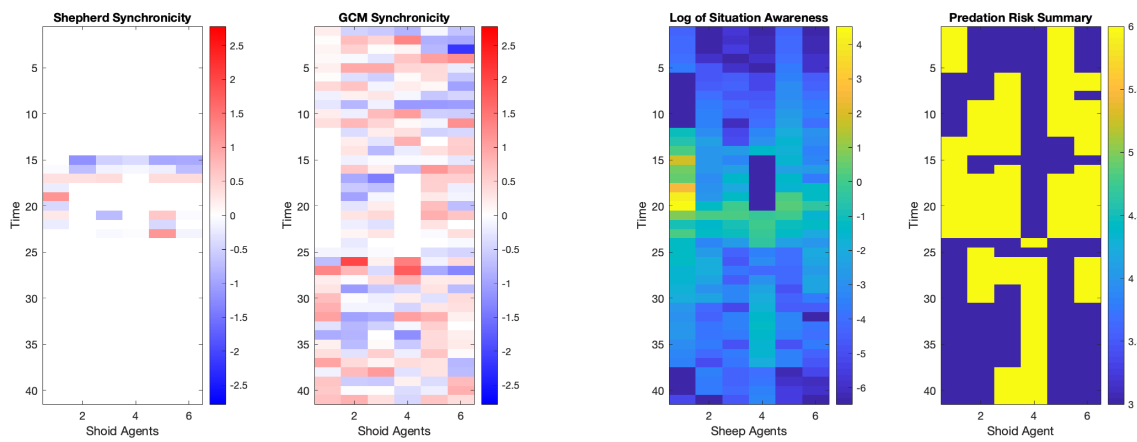

Fig. 4. Predation Risk and Situation Awareness summary measures for a discrete period of contact (live experiment data).

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 to indicate the centre of influence in a herd. 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 model is biologically inspired, based on 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 AI when compared to classical approaches [34]. 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 centre of influence 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 AI, 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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