Fuzzy Approach to Detection of Emergent Herd Formations in Multi-Agent Simulation

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Abstract. In recent years multi-agent modelling and simulation has been suggested as an approach to exploring emergent phenomena exhibited by a variety of systems. A vital part of such an effort is the ability to detect and quantify the particular emergent manifestation under study. As part of a larger study in exploring causal relations in emergent formations, this paper investigates the issue of automated detection of herds in a multi-agent model of large bodied animal dynamics. The proposed solution is based on a fuzzy reasoning approach which incorporates bottom-up and top-down phases as part of the reasoning process. The evaluation of the proposed reasoning method showed that it can be successfully applied for automated detection of herds in multi-agent simulation.

1 Introduction

Group formation is a common characteristic for many social animals. Shaw [1] examined the grouping in fish, where numerous individuals form a social aggregation known as a school. Similar aggregations can be found in birds forming flocks [2], as well as various species of mammals which form herds [3]. Most observations made towards understanding the herd dynamics suggest that both small and large groups rely on local coordination between the individuals to form a herd [4]. Close examination of the behaviour of an individual animal does not suggest that it will join a herd, thus the herd is a novel pattern with respect to the individual animals which comprise it. In addition the herd has functional significance: it decreases the risk of predators and increases the possibility for mating [5]. Therefore given the introduction of novelty and the functional significance, one could argue that the herd is an emergent phenomenon.

The basic idea behind emergence was popularized by Anderson in [6], where he elaborated how global features may arise (emerge) as a property of a system and at the same time be novel to the constitutive components of the system. Emergence can be identified in a variety of systems and processes: from chemical reactions and large scale swarms of social insects to weather patterns and the inner workings of the human brain. In addition emergence is associated with social phenomena like culture, patterns in the news, fashion cycles, stock market exchange crashes and so on. Due to its ubiquity and versatility, the concept of emergence has captured considerable attention in the scientific community. There has been a variety of attempts in different scientific disciplines to observe, predict, control and understand emergent phenomena. Nevertheless due to its intrinsic complexity and unpredictability, emergence is still a scientific unknown. Therefore in recent years, multi-agent systems have been proposed as an approach which could shed light in the process of exploring emergence. The main idea is to use iterative agent-oriented modelling and simulation in order to gradually increase the understanding of a specific emergent manifestation.

In this context the work presented in this paper is a part of a larger effort [7] aimed at the exploration of causal relations between the micro and macro levels, taking herd formation as a particular example. However in order to correlate the emergent behaviour at the macro level with events taking place at the micro level in this example there is a need for a mechanism which would be able to automatically detect groups of animals forming herds. Towards this end we examine different pattern recognition techniques with respect to the requirements and constraints imposed in the study, and we develop a solution to the problem by incorporating both bottom-up and top-down phases as part of a fuzzy reasoning algorithm.

The rest of the paper is structured as follows. Section 2 discusses several issues related to pattern recognition and their relevance to herd detection. The simulation model is presented in section 3, while section 4 presents the design of the proposed fuzzy reasoning mechanism. The performance and the evaluation of the proposed solution is discussed in section 5. Finally section 6 concludes the paper with a brief summary and discussion on the future work.

2 Identification of Herd Formations

Humans can easily detect herds, however teaching a machine to do so is not as simple. The main problem is the inability to arrive at a formally quantifiable definition of a herd which will be generally accepted in different contexts by all possible observers. Nevertheless the field of pattern recognition in the last half a century has come a long way in addressing problems such as this one. The sections that follow contain a brief overview of pattern recognition with emphasis on clustering through statistical analysis. In addition, the applicability of different techniques is discussed in relation to the requirements and constraints imposed by the objectives of our study.

2.1 Overview of different approaches to pattern recognition

In Watanabe's view [8], a pattern is an entity, possibly vaguely defined, that can be distinguished from the chaos. Consequently pattern recognition is essentially a classification (clustering) process. The methods dealing with the identification of patterns can be divided into two main categories: supervised and unsupervised pattern recognition. The supervised methods rely on a predefined (described) set of classes, or already existing set of patterns, which have been classified prior to the recognition process. On the other hand an unsupervised recognition method does not utilize any a priori classification data and establishes the set of classes during the recognition process. According to Jain et al. [9] there are four basic approaches in pattern recognition: template matching, syntactic matching, neural networks and statistical analysis.

Template matching is essentially a procedure where a pattern is compared against a prototype (template) pattern which should be available prior to the recognition process. Although template matching algorithms can allow certain deviations in the pattern from the prototype, they are not suitable for recognizing more substantial variations in the patterns. This is in fact the main problem in applying this approach to herd detection, since the herd pattern exhibits wide variation in shape, size and density.

Syntactic approaches on the other hand rely on a primitive sets of sub-patterns and a set of rules which define how to compose (or decompose) more complex patterns. While this approach is very useful in language recognition, in complex problem domains it requires extremely large training set and computational power [10]. This approach is also not suitable for herd detection because it is impossible to define a limited set of sub-patterns or clear composition rules.

Neural networks offer a rather different approach to pattern recognition. They adopt ideas from biological systems in order to resolve complex non-linear problems. This is achieved through a learning process in which the architecture and the connections between the neurons are updated in order to perform a specific classification task. The main advantage of this approach is efficient and successful classification/clustering of patterns regardless of the problem domain. Therefore given a well established training set, a neural network could be successfully applied to herd detection. However this approach is unsuitable for the purpose of this study, since a neural network does not provide any information on the reasoning process or statistical data on the decision, as suggested in [11].

The opposite is true in statistical analysis for pattern recognition. The recognition methods following this approach conceptualize a "pattern" in terms of multidimensional spatial measures representing the features of an entity to be classified. Consequently the goal in the recognition process is to cluster similar entities together by creating disjoint compact groups [9]. This is the most appropriate approach for addressing the herd recognition problem. Different statistical clustering algorithms are described in more detail in the next section.

2.2 Herd detection as a statistical clustering problem

A general division of the clustering algorithms based on statistical analysis elaborated in [12] suggests four main classes: partitioning methods, hierarchical methods, density based methods and grid based methods. Partitioning algorithms, like *k-means* (also known as HCM) [13, 14] and *EM* clustering algorithm [15], cluster the object set for k input parameters into k clusters in such manner as to minimize the cluster distribution based on a selected mean point. An interesting approach is followed in the *EM* clustering algorithm where, instead of assigning each object to a cluster, a probabilistic membership is computed based on the distance of the object from the mean point. However this method, as well as the rest of these partitioning methods, tends to find clusters of spherical shape with similar size, which do not necessarily represent correctly the natural distribution of objects [13].

Unlike the partitioning methods, the hierarchical methods, like *AGNES* and *DIANA* [16], *CHAMELEON* [17], are based on hierarchical (tree like) decomposition of the object set into smaller sub-sets. While this process is clearly a top-down approach, hierarchical methods can also be applied in a bottom-up way (also called "agglomerative") by starting with each object as a separate group and joining them during the clustering process. The algorithms following this clustering approach do not fall into the same trap as partitioning methods, but they tend to make errors in the assignment of objects to clusters, usually due to the over-simplistic splitting and merging techniques.

By contrast with the previous methods, the density methods are specifically designed to avoid spherical shape clustering and are best suited to discovering arbitrary shaped clusters. This is achieved by treating a cluster as a dense region of objects. The most famous algorithms in this class are *DBSCAN* [18] and *OPTICS* [19]. The major problem of density based methods is a significantly lower efficiency especially in the cases when multiple parameters are taken into account. To resolve this problem grid based methods quantize the space into a finite number of cells, forming a grid structure where the clustering operations are performed. The most famous algorithms in this class are *STING* [20] and *CLIQUE* [21]. While these methods perform quite efficiently (in terms of clustering speed and time) they tend to be increasingly error prone with the increase in the number of clustering parameters.

In addition to the discussed approaches, some methods combine classical clustering algorithms with fuzzy set theory. Perhaps the most famous and most heavily studied fuzzy clustering algorithm is *fuzzy c-means* (*FCM*) [22], based on the *k-means* partitioning algorithm. The main idea followed in *FCM* and similar approaches is that a single entity can belong to more than one cluster. Thus it avoids assigning a particular entity to a single cluster, but rather defines a membership level of the entity to a particular cluster. This approach is particularly useful in problem domains where the boundary between the clusters cannot be clearly determined, like in the case of biochemical analysis of cancer cells [23]. More recent development in the utilization of fuzzy rule based systems for the purpose of data clustering has been done in combination with neural networks. The synthesis of the two approaches has led to the creation of neurofuzzy systems which manage to add readability to the operation of a neural network. For more information on neurofuzzy systems consult [24, 25].

According to Han et al. [12], the selection of an appropriate clustering algorithm depends on several factors including application goals, trade-off between quality and speed and characteristics of the data. Here it has to be noted that herd formation is a special case in the more general context of the study, hence it imposes several requirements for the clustering process:

- it should be done continuously during the model execution, utilizing as less time as possible (preferable maximum around 2 seconds), in order to give to the investigator "real time" visualisation about the model dynamics;
- it should avoid circular shapes and focus on discovery of arbitrary shapes;
- it should process a wide range of densities;
- it needs to evaluate the state of the cluster in relation to a "desired state" defined by the observer (examined in more details in section 2.3).

Given these requirements none of the reviewed spatial data-mining algorithms was found to fulfil completely the requirements. Consequently we moved towards the development of a hybrid approach by incorporating ideas from the data-mining algorithms with other practices in order to match the imposed requirements. The result was a two-way fuzzy reasoning classification algorithm which is described in the next section.

2.3 The role of the observer in detecting herd formations

The emergent behaviour relies on stochastic runtime interactions between the elementary components of the system. The process and effects of emergence can only be observed during system's operation (at runtime) and therefore can not be captured with a model of the system. This creates a fundamental difficulty in devising a criteria or metric for identifying and quantifying emergent formation. Thus the identification of an emergent property or pattern is open to different interpretations. Consequently one can argue that identifying an emergent formation is significantly influenced by the nature of the observer, their capabilities, knowledge and judgement.

This argument also applies in the case of herd detection. On the one hand, herds with strong coherence or extremely loose configurations (which do not form a herd) are immediately distinguishable and clearly identified by most observers. On the other hand, aggregations on the border between an actual herd and a simple collection of single animals are difficult to judge. Thus different observers can have different views whether the same aggregation of animals forms a herd or not. Thus it can be argued that the judgement of the observer directly influences the criteria for detection of herd formations. This is in fact the main reason why the herd recognition algorithm needs to evaluate a particular group of animals in relation to the observer's view of a herd.

In order to resolve this issue, we decided to incorporate the observer's view as part of the reasoning process. The idea is to interpret the results through cut-off threshold boundaries. For example, consider the output variable of the reasoner, called "herd cohesion", which denotes the strength of group. The decision whether this group will be interpreted as a herd or not depends whether the value of the output variable is above the threshold defined by the investigator. The same principle was applied for other input/output variables in the process. Consequently by modifying the boundary values, the investigator can incorporate their own personal judgement into the reasoning process.

3 Overview of the simulation model

The main goal of the herd formation study is to provide insight into how interaction between neighbouring animals translate into observable changes in the global herd pattern. The sections which follow examine the description and specification of the model as well the simulation environment where the model is executed.

3.1 Model Description and Specification

The herd formation model was developed on the basis of the work done by Gueron et al. [4]. The model follows a Lagrangian approach to herd formation, which avoids continuum constraints in favour of discrete individual based modelling. The basic idea behind this approach is that group formation and dynamics is a result of a sequence of decisions made by individual entities. This kind of approach is more appropriate when dealing with large bodied animals [26], compared to Eulerian models where the individuals are expressed through units of volume. Furthermore an individual based modelling approach is more suitable for studying emergent behaviour, due to the fact that it gives an opportunity to correlate the collective behaviour to the individual decisions.

An animal in the model is represented by an agent with two main parameters: movement speed and movement direction. While having the same general direction, the animals have the ability to move laterally left or right. Additionally it is assumed that the model is composed out of homogeneous entities with equal body sizes and movement speeds. Therefore the movement speed and direction at time t for animal A are dependent on *A's* speed, direction and the position of *A's* neighbours at time *t-1*. While there is no explicit message exchange be-

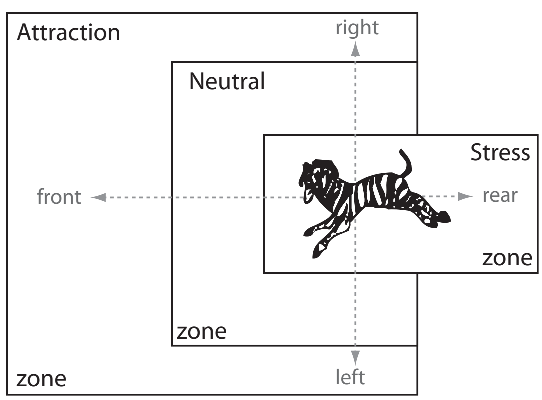

Fig. 1. Overview of the neighbour influence zones, based on [4]

tween the animals, they do interact with each other through modification of the environment by means of spatial repositioning. At the particular time instance only one agent can occupy a particular space in the grid. Therefore based on the position of the neighbours an animal is faced with a set of constraints on where it is able to move. Furthermore the position of the neighbouring animals is vital for the animal's decision where to move next.

The approach followed in [4] defines the decision making process through an evaluation of influence zones. An influence zone is a spatial area on a predefined distance relative to the individual in question. This approach assumes three zones (stress, neutral and attraction), which are depicted in figure 1. A brief explanation of the zones follows:

- **Stress** or personal zone has the highest importance (compared to the other zones) and it is the primary factor which determines the actions taken by an animal. The need for individual space causes individuals to be repelled by their neighbours when their personal space is invaded [27]. Thus depending on the position of the neighbours in the stress zone the animal moves in opposite direction or increases/decreases its speed.
- **Neutral** zone is an intermediate zone which has lower priority than the stress zone. Furthermore, unlike the stress zone, the neutral zone has no rear dimension. This means that the animal does not perceive neighbours in this zone positioned directly behind it. As far as the interaction is concerned, if the neighbours are in the neutral zone the animal does not react and it maintains the same speed and direction. However when all of the neighbours are on the same side, the animal moves toward them. This behaviour according to Hamilton [5] is a display of "selfishness" as the animal is moving towards the centre of the herd in order to reduce the chance of being attacked by predators.
- **Attraction** zone has the lowest priority, it is evaluated only in the case when the stress and neutral zones are empty. Similarly to the neutral zone, it does not have a rear dimension. Neighbouring animals positioned in the attraction zone influence a change in the agent's direction and speed. The presence of neighbours in the attraction zone means that an animal is not part of the herd. Consequently the instinctive response for an animal is to move towards the identified neighbours.

3.2 Model of the individual animal and the simulation environment

Based on the description elaborated in the previous section, the model of an individual animal was developed using X-machine formal notation. An X-machine is a general computational machine introduced by Eilenberg [28] and extended by Holcombe [29]. In many ways it looks like a Finite State Machine (FSM), however it is extended with memory.

A diagrammatic representation of the X-machine model of an individual animal is presented in figure 2. The model does not focus directly on the influence zones, but rather captures the internal decision making structure of the animal.

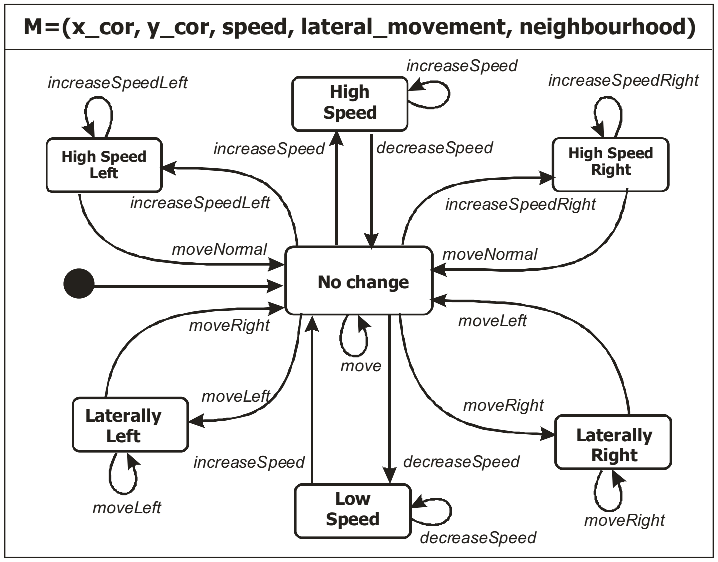

Fig. 2. Diagrammatic representation of the X-machine model of an individual animal. "M" denotes the memory, functions denote transitions between states.

The states represent the movement direction and speed at a particular time instance. While on the other hand the transitions represent a change in the animal's movement speed and/or direction.

Although X-machines are useful and intuitive for modelling an individual animal, a complete computational multi-agent model will need too many states, making the entire model incomprehensible. Furthermore, depending on the complexity, in some cases the task of developing such a model seems nearly impossible. Therefore for the purpose of modelling the multi-agent system as well as execution of the simulation experiments, NetLogo [30] was selected as the most appropriate platform. NetLogo allows modelling and animation of agent like entities in a simulation environment supported by a scripting language, visual animator and data output mechanisms. In addition to the visual animator, which is an excellent tool for observation of the model behaviour (especially in this case, when dealing with herd formation) perhaps the strongest argument for choosing this platform is the correspondence between the X-Machines model encoded in XMDL [31] and the NetLogo scripting language.

4 Fuzzy Reasoning approach to herd detection

In order to address all of the identified requirements (see the last part of section 2.2) for the automated detection of herd formations, we have developed a supervised fuzzy reasoning mechanism. The main reason for adopting this direction was the need to incorporate the observer's judgement as part of the process and vaguely defined classification criteria at the same time. Consequently we took advantage of the fuzzy set theory in order to utilize inherently inexact concepts as part of the reasoning process. For example, using a fuzzy approach one might express the following criteria: in order for a group of animals to form a herd, the members of the group need to be "very close" and the group should have a "sufficient" number of members. Furthermore this tolerance for imprecision can be exploited to achieve tractability, robustness and better human-computer interaction [32].

It has to be noted that our approach is quite different from the fuzzy clustering paradigm. We apply concepts from fuzzy set theory to deal with the imprecise nature of the herd clustering criteria rather than using it to express fuzzy membership functions. Thus, in the developed recognition scheme each entity is assigned to a single cluster and does not possess membership levels to multiple clusters. Furthermore, since in our study the emphasis is on herd formation as an emergent phenomenon, our approach combines bottom-up and top-down directions as part of a two-way reasoning process, in accordance to the arguments put forward by Conte and Castelfranchi in [33]. A brief overview of the developed reasoning algorithm is presented in figure 3. Although the operations in the reasoning process are sequentially interconnected, they can be logically divided into three major phases.

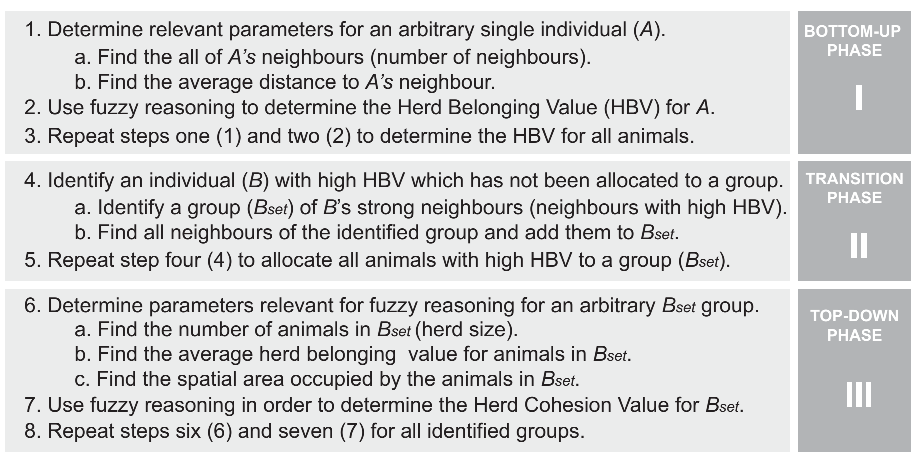

Fig. 3. The developed reasoning algorithm for automated herd detection

The initial stage in the process is the bottom-up reasoning phase. It is depicted by steps 1 through 3 in figure 3. The goal of this phase is to evaluate the preference of an individual animal to be part of a herd. Towards this end, two major factors (properties) of an animal are taken into account. The *aver-*

age neighbour distance represents the average spatial distance to all neighbours of a given animal, while the second parameter is the *number of neighbours*. In this context, a neighbour of an animal A are all animals which are located either in the stress or neutral zone of animal A. The attraction zone is not taken into account since there is an obvious spatial gap between the animals. These two parameters represent the input fuzzy variables in the bottom-up reasoning phase. The output variable, called "Herd Belonging Value" (HBV), denotes the preference for a particular animal to be a part of a herd. There is a total of 54 reasoning rules which assign a single fuzzy set for each of the two input variables with a corresponding fuzzy set in the output variable. Figure 4 shows the mapping for the input variables and the corresponding fuzzy set in the input variable. As can be seen from the figure, the value represented by the output fuzzy set has forward correlation with the increase in the number of neighbours (from *weak_low* to *strong_high*) and reverse correlation with the increase of average neighbour distance (from *strong_high* to *weak_low*). In other words the HBV increases with the increase in the number of neighbours and decreases with the increase of the average neighbour distance.

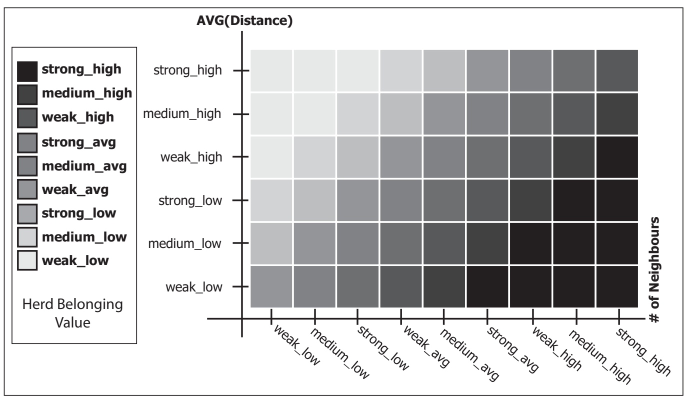

Fig. 4. Rule mapping of the fuzzy sets for the input variables (*Average Neighbour Distance* and *Number of Neighbours*) on the fuzzy sets of the output variable (*Herd Belonging Value*).

The second phase, depicted by steps 4 and 5 in figure 3, is the transition from the evaluation of an individual animal towards reasoning about a group of animals. In this phase the crucial point is the identification of groups of animals which could potentially form a herd. The identification of the group is primarily depended on the animal's preference to be part of the herd which was evaluated in the bottom-up phase. The HBV is used to determine a set of animals which are called "strong neighbours". A strong neighbours group represents a set of neighbouring animals with an HBV above the threshold defined by the investigator. The group of strong neighbours forms the skeleton of the possible herd. The process continues with the expansion of the group by adding animals (with low HBV) which are neighbours to the animals in this group. The rationale is that the strong neighbours form the core of the herd while the animals with low HBV form the edge of the herd. In this manner the final result of the process is a group of spatially connected animals. The phase completes when all animals with HBV are allocated.

Once the groups of animals are identified the process continues with the top-down reasoning phase. This phase is captured by steps 6, 7 and 8 in figure 3. The goal of this reasoning phase is to evaluate the coherence of each group of animals. The decision whether a particular group forms a herd or not is determined by the value of the output variable ("herd cohesion") and the thresholds defined by the investigator. In addition to the *average HBV* of the group, also the *group size* and the occupied *spatial area* are used as input variables in the reasoning process. Herd size denotes the number of animals in the group. Herd area denotes the size of the spatial area that is occupied by the animals in the group. A decrease in the group's area implies an increase in the herd cohesion of the group. The reasoning rules which determine the mapping between the fuzzy sets for the input variables and output variable follow the similar gradation as in the case of the bottom-up phase but with one extra dimension.

5 Evaluation and Discussion

The discussed design of the fuzzy reasoner was implemented as a Java-based extension to the Netlogo simulation model. It uses the FuzzyJ libraries [21] in order to support the fuzzy reasoning process. The evaluation of the reasoner was done in two steps. First of all the implementation of the reasoner was tested using unit tests which evaluated the influence of a single input variable on the output variable. The results of this testing led to revisions in the fuzzy set distribution for certain input variables.

The second step of the evaluation was focused on the reasoner's ability to detect herd formations during the execution of the model. A major constraint in this process was the fact that clear-cut "correct" output could not be determined due to the nature of the herd detection problem. Consequently the intuition of the investigation team on herd formation patterns was used as basis for comparison. Thus the process was based on an estimate of how closely the developed reasoner matched what the investigators considered to be a herd in a given context.

In simulation scenarios with near optimal values the reasoner performed very well. It managed to clearly differentiate between loose groups and herd formations, as can be seen in the screen capture examples in figure 5. In regards to the computational time required, it needed on average about 0.7 to 1 second to animate the model and detect the herds for population of 200 and about 3 to 4 seconds for population of 400 animals. Consequently it fulfilled the imposed requirement by allowing the investigator to observe in "real time" the model

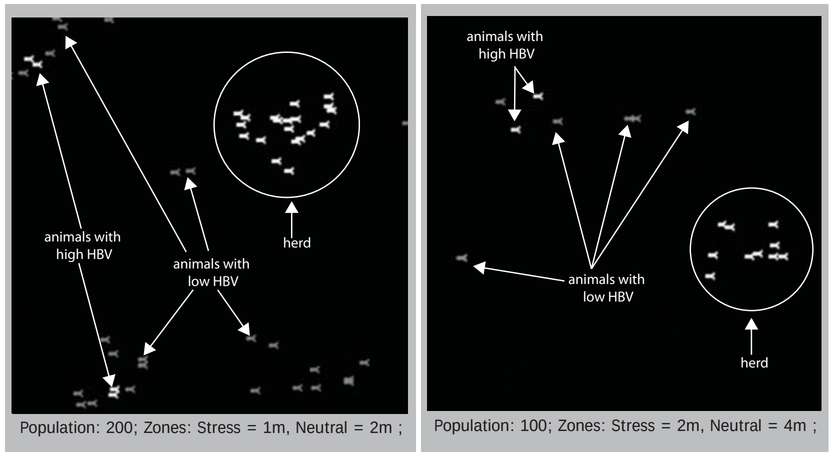

Fig. 5. Partial screen capture of the herd recognition during model execution. Labels and arrows are added for presentation purpose.

animation. Furthermore the algorithm managed to discover arbitrary shapes, as can be seen in figure 5. However, several simulation scenarios revealed problems when the animal population was an extreme (approximately populations below 20 and above 200). While to some extent the reasoner was designed to compensate for the population flux, it failed to properly identify herds for extreme population density. In order to resolve the issue there is a need to incorporate population density function as part of the reasoning process. To this end work is ongoing to express the scales of the fuzzy variables in terms of a a function of the population density.

Another problem which became apparent during the evaluation was the identification of groups of animals that might form a herd. The initial approach where a permutation of the subgroups of the main group was considered proved to be computationally too expensive and time consuming (it needed up to 15 minutes for a single time frame when the population was 400). Although this practice allowed the recognition of subgroups as herds on their own, comparison with the case where only the entire group was processed showed that it had only a minor impact. It clustered subgroups as herds in a very rare cases and only for very limited time interval (a few time steps at best). Therefore in order to maintain the efficiency of the reasoning process, the algorithm presented in this paper does not reason about subgroups. A possible solution to this problem is to avoid brute force permutation by implementing heuristics which will reduce the number of subgroup permutations. However there is a need for additional work which will determine the usefulness of this approach in respect to the required computational efficiency.

6 Conclusions and Future Work

Emergence is one of the most intriguing and at the same time least understood phenomena of complex systems. However since it is visible only at runtime, detecting and quantifying emergent manifestations is a vital part in any attempt to explore and analyse emergence. In this context, the work presented in this paper examined issues related to the automatic detection of emergent herd formations in a multi-agent simulation. Detection of herd formations is essentially a pattern recognition problem, however none of the generic recognition approaches managed to match completely the specific set of requirements imposed in the study.

Consequently we developed a supervised two-way fuzzy reasoning mechanism, by utilizing both bottom-up and top-down processes in order to detect herd formations. Our method differs from fuzzy clustering approaches in the sense that it uses fuzzy concepts in order to deal with vague clustering criteria rather than expressing fuzzy membership to a cluster. Furthermore our approach incorporates the observer's view as an important part of the reasoning process, which to the best of our knowledge is a novel way of dealing with a clustering problem. The evaluation of the reasoner showed that it can be applied successfully for automated detection of the herd pattern in a multi-agent simulation of animal dynamics. Nevertheless in some cases, where the population density was extreme, it failed to produce the desired results.

Although the solution we have presented in this paper is by no means a generic clustering mechanism nor a general solution to recognition of emergent manifestations, it can be utilized to solve similar problems in detecting emergent cluster formations in distributed agent based systems. In a more general view, our approach to clustering can be beneficial in detection of clusters in a variety of networks exhibiting small-world characteristics like in a number of social networks, gene networks, telephone call graphs and so on.

The resolution of the problems identified during the evaluation (see section 5) is planned as an initial step of the future work. The main idea is to express the fuzzy variables through a function of the population density. Additionally we plan to investigate the possibility of implementing heuristics for subgroup identification. Once this work is completed, the herd pattern classifier will be used as part of an experimental investigation of causal relations in the study of herd formation and dynamics.

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