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Towards Decentralised Detection of Emergence in Complex Adaptive Systems

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***Abstract*—Complex Adaptive Systems are systems composed of distributed, decentralized and autonomous agents (software components, systems and people) and exhibit non-deterministic interactions between these agents. These interactions can often lead to the appearance of "emergent" behaviour or properties at the system level. These emergents can be harmful to the system or individual constituents, but are by their nature impossible to predict in advance and must therefore be detected at run-time. The characteristics of these systems mean that detecting emergence at run-time presents a significant challenge, one that cannot be met by existing methods that depend on a centralized controller with a global view of the system state.**

In this paper we present an important step towards decentralised detection of emergence in Complex Adaptive Systems. Our approach is based on observing the consequence of naturally arising feedback that occurs from the system level (macro) to the component level (micro) when emergent behaviour or properties appear in a system. This feedback results in the appearance of correlations, where none existed before, between the internal variables of individual agents and the properties that an agent detects in its local environment. In a case study of five different multi-agent systems we demonstrate that the number of agents that report these correlations increases as emergence occurs in each system.This provides the constituent agents with sufficient information to collaboratively detect when emergence has occurred at a system level without the need for a centralized, global view of the system.

***Keywords*—Emergence, detection, complex adaptive systems, decentralised**

I. Introduction

The last decade has seen Complex Adaptive Systems (CAS) emerge as the next generation of software systems. These systems are made possible by advances in computation and interoperability and can span organizations and large geographic areas with no centralised controller or monitor [1]. They emerge organically from non-deterministic interactions of independent heterogeneous components, systems and people. These constituents behave in different ways, responding to an ever-changing environment as they pursue individual goals that can be conflicting to the goals of other components and the system as a whole. The organic and non-linear nature of their interactions means that predicting the characteristics and behaviour of these systems becomes impossible with any great degree of accuracy [2] [3].

This unpredictability is a significant challenge when we need to detect emergence, a hallmark of these systems [4]. Although there exists no universally accepted definition of emergence, it can be summarized as a characteristic of systems where properties and behaviours (emergents) appear at the system (macro) level that were not explicitly implemented. These emergents occur dynamically from the interactions between entities at component (micro) level, and cannot be reduced to the properties or behaviour of the individual entities [5]. Typical examples of emergent behaviour include traffic jams and swarm formation of birds and fish [6]. The interactions of agents at the micro-level are said to have causal power on the emergents at the macro-level. However, the macro-level can also have a causal power on the micro-level, i.e., downward causation, where the emergent phenomenon constrains the entities at the micro-level [7]. The impact of a traffic jam on a constituent car provides a way of thinking about this relationship. The car contributes to the volume of traffic causing the emergent behaviour, and this emergent behaviour impacts the car by limiting its speed and also, possibly, the route it will take.

Detecting and potentially shaping this emergence is a fundamental challenge in CAS to avoid possible harmful behaviour. Existing methods to handle emergence have focused on attempting to predict it through modeling and simulation of large multi-agent systems [8]–[10]. However, such approaches are limited in their effectiveness as the CAS motivating this paper are inherently unpredictable in their nature and require detection at run-time. Other techniques for detecting emergence have used various statistical methods on system variables that represent global features of the system [11]–[17]. However, these approaches depend on a centralized system monitor with access to global system state information, neither of which is possible in CAS that are distributed, and composed entirely of decentralized autonomous agents.

This paper addresses these limitations by providing an important step towards facilitating decentralized detection of emergence in CAS. We use the concept of downward causation, where emergent properties provide feedback to the system's constituent components, acting to constrain behaviour at the micro level of the system [7], [18]. Our approach enables the constituents to detect this feedback by monitoring relationships between their internal variables and the variables they sense in their local environment. **We hypothesize that this feedback results in the appearance of correlations between these variables when emergence occurs, where no correlation previously existed.**

The remainder of this paper is organized as follows. Section

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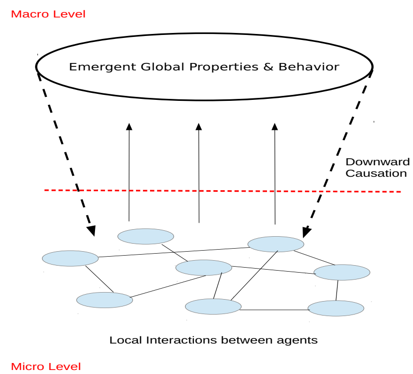

Fig. 1. Bi-directional relationship between micro and macro-levels

II discusses emergence in CAS and the challenges in detecting it. Section III presents the current state of the art. Section IV outlines our hypothesis that emergence results in new correlations detectable by individual agents. Section V and VI present an evaluation, which is based on experimentation across five multi-agent system models, and the results obtained. Section VII provides a discussion of these results. Finally, Section VIII concludes the paper and outlines our future directions.

II. Emergence in CAS

This section describes what is meant by emergence and the concepts associated with it that are fundamental to this paper. There is a large body of literature that attempts to define and characterise emergence in varied domains such as social sciences, philosophy and computational science. This paper is limited to emergence in computational science, with space only permitting a brief discussion. Interested readers can find more comprehensive accounts in [6] [19] [20] [21].

Emergence and self-organization are phenomena that characterise CAS [22]. Despite this, no widely accepted definition of emergence exists, though a number of characteristics are common across the literature [6]. Emergence can only occur in systems composed of autonomous parts, agents, who interact in dynamic, non-deterministic ways. These systems are composed such that it is possible to talk about them at two levels; the level of the individual agents (micro) and the level of the global system (macro). Emergence occurs when interactions at the micro level result in properties or behaviour (emergents) at the macro level becoming observable, and these emergents are novel with respect to the individual agents.

A taxonomy of different types of emergence can be defined from the relationship between the micro and macro levels [23]. These are: *nominal emergence* (where the micro causes the macro level phenomenon) *weak emergence* (where the macro level feeds back onto the micro level) and *strong emergence* (where the micro-level agents learn and adapt to this feedback). This relationship between the micro and macro levels is illustrated in Figure 1. Strong emergence is the most significant type of emergence that is encountered in CAS, and it results in the systems as a whole becoming reflexive. Muller [24] distinguishes between weak and strong emergence by who is detecting the emergence. In weak emergence, the observer is outside the system looking at the overall system state from a global viewpoint, for example, a human observing a path made by an ant colony between their nest and a food source. With strong emergence, the agents themselves are the observers of emergence, identifying a phenomenon at the macro level that represents an evolution in the system. The agents' capacity and target of observation must be sufficiently broad to be capable of identifying the phenomenon as global rather than local. However, the identification of these phenomena involves a change in behaviour and so a feedback or bi-directional link is created. To return to the ant colony example, for strong emergence, individual ants would identify the emergence of the path but to do so they would require a map of the area between the nest and the food source, and not just what they perceive locally.

Cognitive agents can be used to detect these phenomena if they are themselves part of the system. However, the characteristics of CAS and emergence means that this task is non-trivial to accomplish. Such systems are composed of many parts and subsystems that interact nonlinearly in ways that are difficult to recognise, manage and predict [25]. This unpredictability results in unforeseeable connections and subsystems forming organically at run-time, and is compounded by the inherently unpredictable nature of the emergence that results. This means that it is not possible to deploy specially appointed agents to detect emergence, as it is not possible to know what to look for in advance.

The decentralised nature of CAS also presents an obstacle to such 'lookout' agents. This is especially the case if we consider city-scale CAS, such as the Smart Grid, water management systems or intelligent traffic management systems. Obtaining a global view of the system state to determine the existence of emergents becomes impractical, as that system state is constantly changing. Instead, agents who try to detect emergence should rely on locally available information, which is more timely, and collaborate with other agents to determine together if emergence exists in the system.

III. State Of The Art

This section provides a short discussion on existing research in the area of detecting and predicting emergence. Our analysis is informed by the characteristics of CAS outlined in the previous section. These require emergence detection to be decentralised and occur at run-time.

A. Variable-based approaches

The first of these categories use system variables and statistical analysis, similar to the work described in this paper, to determine the existence and extent of emergence in a system. However, these approaches require a centralised architecture and focus on system-wide properties to provide these variables, making them unsuitable for the detection of emergence in CAS at run- time. Such an approach is provided in [11], where a mathematical theory is described for representing strong emergent properties of a system by measuring system entropy at different levels of abstraction. Entropy measures are also used in [12] and [13], however both depend on knowledge of the global system state to calculate these measures.

Seth [14] uses linear and non-linear time series analysis based on Granger Causality to define G-Emergence. This approach defines a macroscopic property, such as the centre of a group of birds, to be emergent when it is both statistically autonomous and statistically caused by the microscopic properties (individual position of each bird). Chan [15] notes the fundamental importance of interactions between agents in creating emergence in any system, and attempts to detect emergence by monitoring a time-series of interactions and state changes across all agents in the system. Emergence is said to exist when this interaction metric departs from normality.

De Wolf et al [16] present a hybrid method for providing guarantees about system-wide behaviour in decentralised autonomic computing systems. Their approach allows users to observe the evolution of macro-level properties when accurate models of micro-level properties are provided. It requires users to have knowledge of relevant variables in advance and that system-wide variables are obtainable. Finally, [17] describes "Angle", a hierarchical framework to detect emergence in distributed clustered systems. Emergence is defined to occur at a change point in time-series data. Although this framework is more distributed than others discussed here, the monitoring and analysis are done by static nodes, which limits its applicability to CAS as such systems are open and contain a high degree of volatility across agents.

B. Formal approaches

The second category of techniques use formal approaches to define and predict emergence. An early example of this is provided in [8] where a formal grammar is used to define weak emergence. Emergence is defined as properties that are produced by agent interactions but cannot be derived by summing individual behaviours through a superimposition of all individual agent languages on one another. This approach is heavily centralised and requires all possible agent behaviour to be known and to remain unchanged throughout the systems lifecycle. Additionally, the use of superimposition leads to state-space explosion causing the approach to be computationally expensive. The state-space explosion is addressed in [9], where the approach is improved by limiting analysis to only those states that are possible and of interest. However, this assumes that these states can be predicted in advance which is not the case in CAS.

Finally, in [10] the authors present a model-based technqiue with the goal to detect emergent behaviour at system design-time. Detection at this stage can be used to determine the cause of the behaviour and thus eliminate or control the emergence. Emergence here is represented by implied scenarios, types of behaviour, that are in the synthesised model of the system but are not explicitly in its specification as a scenario.

C. Event-based approaches

The final category of detection methods are event-based and are hybrids of the other categories presented here, incorporating both statistical and formal approach aspects. However, similar to those categories the approaches here rely on centralised architectures and a significant level of knowledge at design time making them unsuited for emergence detection at run-time in open CAS.

Chen et. al [26] provide a method for describing emergent behaviour at different levels of abstraction based on defining event types, and differentiating between simple and complex events. This allows correlations to be discovered between these event types in simulations to identify relationships across abstraction levels of the system. Their approach requires event types to be defined in advance with an additional requirement for extensive simulation to determine correlations. Finally, [27] describes an approach to detect emergent unwanted behaviour in games at runtime by monitoring the system and determining if it conforms to a set of designer specified constraints.

Our approach, which is outlined in the next section, improves upon the work discussed here by showing that all agents who form the micro-level of a CAS can be used to detect emergence. This detection is possible using locally available information only.

IV. Detecting Downward Causation

In this section, we outline an important step towards facilitating decentralised detection of emergence by enabling the constituent agents, already comprising the system, to act as the detectors. Our hypothesis is based on the bidirectional link that exists between the two levels in the system, and in particular the downward causation that results from the macro to the micro level. This concept states that an emergent phenomenon, that exists at the macro level, impacts the components at the micro-level by constraining their behaviour, or their environment in some manner. For example, the direction a group of ants move in, will become ordered when a path between their nest and a food source emerges. We assert that it is possible for individual agents to detect this constraint when it occurs, as its relationship with its environment, including other agents, will alter in some detectable way. Once detected, agents can collaborate by sharing their individual experience of this constraint. In this fashion, the agents can aggregate a sufficiently broad system view, as required by Muller [24], to observe the emergence of global behaviour and patterns.

To do this we propose to use statistical analysis of variables that can be observed by each agent in its locality. Specifically, we ask each agent to monitor variables that they possess internally (representing their state), and variables that they acquire from their immediate local environment, which represents the state of that locality. We use a sliding window approach to monitor these variables, as illustrated in Figure 2, where a time series of 20 values is collected for the two variables, X and Y. An analysis is then undertaken to determine if a correlation exists. Once the analysis is complete, the earliest 5 values in each time series are discarded, with subsequent analysis occuring once five new values are obtained.

In particular, our analysis uses the Pearson product-moment correlation coefficient, a measure of the linear dependency between two variables and is calculated using the covariance of the two variables and their standard deviations:

$$r = \frac{cov(x, y)}{\sqrt{\sigma(x)}\sqrt{\sigma(y)}} \quad (1)$$

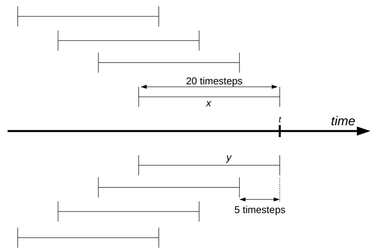

Fig. 2. Sliding window approach used

where

$$cov(x, y) = \sum_{t=1}^{N} \frac{(X_t - \overline{X})(Y_t - \overline{Y})}{N} \quad (2)$$

Our hypothesis is that emergence will result in the appearance of statistically signifcant correlations (where none existed before) between variables locally available to the agents. Correlations are statistically significant when the correlation coefficient between the two variables has a P-value $<= 0.05$. The appearance of these correlations is the result of the downward causation (constraining feedback) from the macro to the micro level which changes the relationship between these variables. In the rest of this paper we present a case study to explore this concept with a set of 5 multi-agent systems. The selection of suitable variables to monitor is a significant challenge and in future work we intend to explore means of providing agents with a model for an independent means of achieving this. However, for the work described in this paper we have hand selected variables for each model outlined. This is done to enable us to determine if emergence results in correlations that are detectable by individual agents using only locally available information.

Note, a single agent detecting a statistically significant correlation between these two variables is not sufficient to make an assertion about emergence. We argue that a significant proportion of agents will simultaneously experience the appearance of correlations in their locality and through collaboration and cooperation it is possible to aggregate their individual local experiences to reason about the global system. Our future work will explore efficient approaches to achieve this. Existing distributed agreement protocols such as Gossip [28] or byzantine consensus [29], or ergodicity measures [30], which have been applied to emergence [31], provide interesting start points.

V. Experimental Setup

In this section we describe each of five well-known multi-agent systems implemented to evaluate our hypothesis. For each, we briefly outline the characteristics of the system, what is meant by emergence in this model and the variables we monitor during our experimentation. All models discussed were implemented using NetLogo [32]. Additionally, a plugin for the R-project [33] is available for NetLogo, providing the framework for the correlation analysis undertaken by each agent in our simulations.

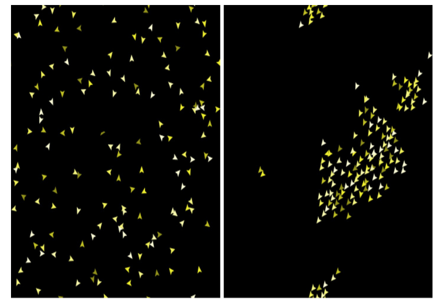

Fig. 3. Flocking model - simulation screenshots

A. Flocking

1) Model Overview: The first model we use in our evaluation is flocking [34], which simulates the aggregate behaviour in boids (birds or fish) when interacting in groups. The emergence in this model occurs, when patterns form in the aggregate behaviour such that the flock appears to move in unison. When implementing the model, each boid is represented as an autonomous agent, with the formation of flocking patterns being achieved through the local interactions between these agents. This is illustrated in Figure 3, where the image on the left provides a screenshot of the model with no flocking behaviour present, while the image on the right displays compelling flocking behaviour.

In this model, interactions between agents occur when agents are located in close proximity to each other. When this occurs, each agent makes an individual decision to alter their course, based on three rules:

1) **Separation**: Steer away from other agents that are too close.
2) **Alignment**: Steer so that they are moving in the same direction as agents nearby
3) **Cohesion**: Steer towards the centre of other agents nearby

The separation rule is given precedence over the other two rules such that if an agent A perceives another agent B to be too close, Agent A will only separate and will not align and cohere at that timestep. However, if Agent A deems no other agent to be too close, it will align and cohere with other agents in its locality.

2) Implementation: Our simulation uses 150 agents in a squared environment (sized 50x50 units) that wraps both horizontally and vertically. This allows agents that fly through any border of the environment to appear again seamlessly from the other side. At each timestep all agents update their heading using the three rules defined above before moving 1 unit forward in that new direction. Figure 4 shows the field of vision of each agent in the model. All agents can see other agents only within a five unit radius from their centre point (the outer cirlce). Agents apply the model rules based on the agent set found inside this threshold. An agent will deem another agent to be too close when they are within 1 unit of their own position (the inner circle), triggering the seperation rule.

3) Correlation Analysis: Heading, the direction of travel, is a fundamental concept to every agent in the model. We selected

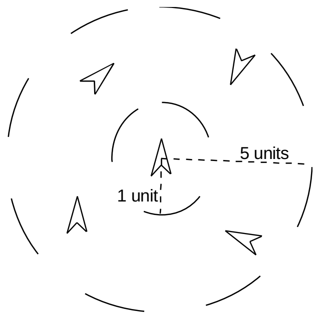

Fig. 4. Field of vision for flocking agents

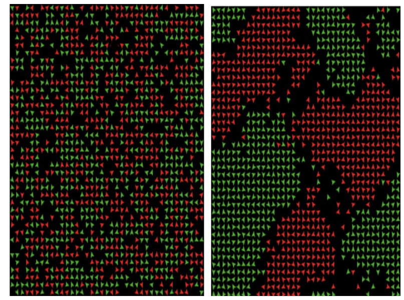
Fig. 5. Segregation model - simulation screenshots

this to provide both variables that each agent monitors. For the internal variable, the agent uses its own heading at time, t. The environment variable is derived by the perceived heading of the centre-of-mass (average (x,y) position) of all other agents in an agent's locality at t. This locality is defined by the agent's field of vision. To derive this, the agent calculates the position of the centre-of-mass at t. This position is subsequently compared to the position of the centre-of-mass at time $t + 1$, allowing the agent to determine the "heading" of the centre-of-mass at time t. The requirement of having other agents in the locality to derive our environment variable means that we only record internal variables when a corresponding environment variable is also available. A statistically significant correlation will appear here when the heading of an individual agent is no longer independent from the aggregate heading of the other agents in its locality.

B. Segregation

1) Model Overview: Schelling's model of spatial segregation [35] is a model of emergent phenomenon resulting from the interactions of individual discriminatory choices. The model, a pioneering work in social science, demonstrates that segregationist structures (ghettos) can emerge spontaneously through the dynamics of these interactions without the individual agents requiring any preference for ghettos.

The model is composed of agents, each characterised by one of two colours, and the environment divided into cells, similar to a chessboard. Each agent resides in one of these cells with only one agent permitted per cell. The structures that form, after a series of interactions, are contiguous blocks of similarly coloured agents. This is illustrated in Figure 5 where the image on the left shows an initial state with no discernible pattern and the image on the right shows that agents have clustered in groups based on the same colour.

The colour of each agent provides the basis for their decision making and interactions with other agents. At each timestep, an agent counts the number of agents in neighboring cells with the same colour as themselves. If this number is below a certain percentage of total neighboring agents, the agent makes a decision to move to a random free cell nearby. By adjusting this threshold proportion, contiguous blocks of similarly coloured agents will form, with the formation of ghettos, representing emergence in the model.

2) Implementation: The movement of agents during each simulation is entirely random. If an agent decides that it wants to move to a new location, because the number of similarly coloured neighbours is too low, it first randomly selects a direction to move (between 0 and 360 degrees). Next the agent randomly selects a distance to travel up to a maximum of 2 cells. The agent checks if the cell at that location is free and if so, the agent moves there. If the cell is occupied, the agent selects a new random direction and distance to look in. Our implementation uses 2090 agents interacting on a square environment consisting of 2601 cells, giving a coverage of 80% of the environment.

3) Correlation Analysis: In this model, an agent uses the randomness associated with its movement in order to derive two variables to monitor. Each agent has a sense of direction as it must select a direction of travel before it can move. This provides each agent with a concept of having a front (ahead of) and back (behind) and we use this to derive variables for each agent to monitor for the appearance of correlations. At each time step, before an agent makes a decision to move or not, it randomly selects a heading and counts the number of free cells within a radius of 5 cells to the front and back. These variables indicate the amount of freedom an agent has to move or not, as a small number of free cells means they have limited opportunity of where they can move. The heading changes randomly at each timestep which means that the direction of what's in front of, and behind the agent will also change randomly at each time step. This variation in the monitoring process means that an agent's heading does not become stagnant, as would occur if it only changed when the agent moved. Statistically significant correlations will only appear when the variation in the number of free cells on either side of an agent are no longer statistically independent.

C. Ant Colony

1) Model Overview: This model simulates the foraging of ants between their nest and food sources with agents (ants) in this model interacting indirectly through their environment (stigmergy) [36], [37]. When the model is initialised, agents move randomly until they find a food source at which point they carry the food back to their nest, depositing a slowly evaporating pheromone in the environment on the way. This pheromone is detected by other agents, creating interactions, and is used to find the food source. The accumulation of pheromones as more agents reinforce the path leads to the ant colony finding the shortest path between their nest and food sources. The establishment of these paths, a concept not apparent to the individual agents, represents emergence in this

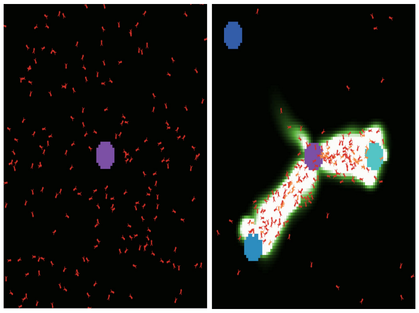

Fig. 6. Ant Colony model - simulation screenshots

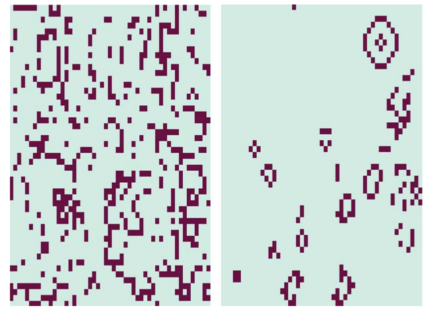

Fig. 7. Game of Life model - simulation screenshots

model. This is illustrated in Figure 6 where the image on the left shows a random distribution of ants with no food sources present and only a nest (purple). However, the image on the right has food (blue) present, and illustrates that the emergent trails have appeared (green).

2) Implementation: Our simulation uses a population of 200 individual agents with all agents produced by a single nest. Agents wander around the environment randomly until they find a food source or detect pheromones in the environment. We initialize our simulations with no food sources present, instead adding three food sources after a number of time-steps have elapsed. This provides each run with a bedding-in phase during which no emergence will occur, allowing us to compare data before, and after emergence appears in the model.

3) Correlation Analysis: Our approach in this model is similar to that used in the flocking model presented before. Agents monitor their own heading change, and the heading change they perceive of centre-of-mass of other nearby agents at the same time step. These two variables are maintained by each agent throughout each simulation with periodic checks made to test for statistically significant correlations between them.

D. Game of Life

1) Model Overview: Conway's "Game of Life" Cellular Automaton [38] provides our next model. This model represents a significant departure from the rest of the models used in the case study presented here, as agent mobility, a defining characteristic of the other four models, is absent. This model is comprised of a set of reactive agents, cells, that can be either "alive" or "dead" depending on the number of "alive" neighbouring cells. Alive cells die if their location is overcrowded or under populated, while dead cells become alive if there is a specific number of alive neighbours.

In this model, the emergent properties are patterns that are formed by living cells. This is illustrated in Figure 7 where the image on the right shows emergent patterns that are clearly visible. These patterns, such as gliders and blinkers, can appear dynamic, giving the impression that they are moving across the grid of cells. This dynamism is not a feature of the agents that generate the patterns. The agents themselves are stationary and always in one of two states, "alive" or "dead".

2) Implementation: Our enviroment consists of 2600 cells arranged in a typical grid formation. Agents in simulation follow three simple rules that govern their interactions with their neighboring agents. These are:

1) A live agent will remain alive if the number of live neighbours it has is between a lower threshold A and an upper threshold B
2) A dead agent with exactly the correct number of live neighbours, C, will become alive
3) Otherwise the agent will die of either loneliness or overcrowding.

where $0 \leq$ A,B,C ≤ 8 and A $<$ B.

3) Correlation Analysis: In this model the concepts of internal and environment variables is not trivial due to the limited number of states and actions each agent posseses. Therefore, an agent in our implementation monitors its live-state, whether it is alive or dead, at each timestep. The agent also records the live-state of its neighbourhood by counting the number of neighbouring agents who are alive or dead. If the number of alive neighbours is greater than or equal to the number of dead neighbours the agent records that its neighbourhood was alive at that timestep. The number of alive states for both variables is counted using a sliding window approach with perioidic checks made for statistically significant correlations between the two.

E. Gas Particles

The final model used in our experimentation models the movement of gas particles in an enclosed space [39]. The model is similar to a billiard table, with each circular particle possessing mass and an initially random direction and velocity. A screenshot of the model is provided in Figure 8, where the velocity of particles is indicated by its colour. The movement of particles cause them to collide, both with each other and with the border of the environment (highlighted in yellow). These collisions, or interactions, change the direction and velocity of the involved particles. However, despite the seemingly complex nature of the behaviour in the model, interactions between particles are deterministic, obeying the known physical laws that govern collisions between objects in reality. As the model is deterministic, no emergence occurs and we include it here to provide a test case under which we can evaluate our approach where no emergence will occur.

1) Implementation: Our simulation consists of 180 agents (particles) interacting in a closed environment sized 80 x 80 units. All agents are initialised with a random direction and

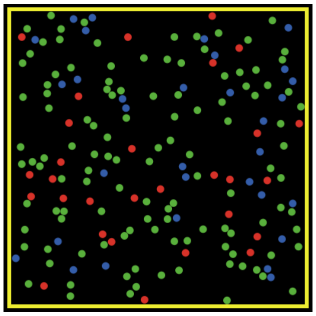

Fig. 8. Gas Particles model - simulation screenshot

velocity. Although it is possible to randomise the size and mass of agents, our environment imposes uniformity for these characteristics across all agents.

2) Correlation Analysis: Similar to the models described before, heading is a characteristic of agents in this model so we again use it as the basis for correlation analysis during our simulations. At each time step, all agents record their own heading and the average heading of agents within their locality, defined to be a radius of 5 units from the agents' centre. The agent monitors these two variables throughout the simulation and reports if statistically significant correlations appear.

VI. Experimental Results

In this section we present the results of our experimentation for each of the models presented in the previous section. A uniform simulation length of 800 timesteps was used across each of the models to facilitate comparisons between results obtained. Additionally, each of the 4 models that exhibit emergence (flocking, segregation, ant colony and game of life) were run in two configurations, one that generated emergence and one that didn't. The data generated during these non-emergence runs, in addition to the non-emergent gas particle model, provides a baseline of the number of agents that report statistically significant correlations across the models in the absence of emergence.

For each simulation there is an initial seeding period where agents are compiling enough samples of each variable being monitored before they can run the first correlation period. Due to the characteristics of each model, the length of this period is not uniform across all models nor is it uniform for all agents inside the same model (for example, agents will only record variables in the flocking model when there are other agents within its field of vision). As a result, we exclude the first 200 timesteps when summarising the results of our experimentation in Table VI, including the final 600 timesteps only. We found a significant increase in the percentage of agents reporting statistically significant correlations across all models when emergence was present.

TABLE I. Percentage of Agents Reporting Statistically Significant Correlations

Model	No Emergenge				Emergence			
	Min	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**
Flocking	2.7	18.0	10.1	2.5	19.4	54.0	37.8	7.0
Segregation	9.3	16.0	12.8	1.8	13.8	62.1	29.6	12.7
Ant Colony	7.5	19.5	12.1	2.7	15.5	51.0	35.5	7.5
Game of Life	4.5	6.8	6.0	0.5	2.7	30.9	18.1	9.1
Gas Particles	0.6	8.3	4.3	1.5	N/A			
Average	**4.9**	**13.7**	**9.0**	**1.8**	**12.8**	**49.49**	**30.4**	**9.0**

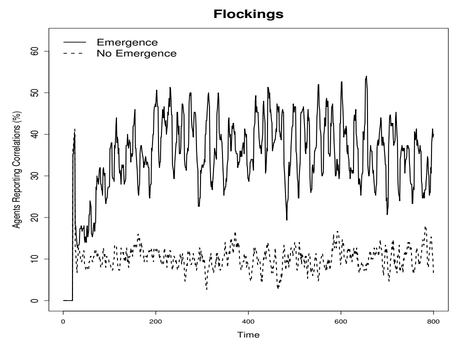

Fig. 9. Flocking Results

A. Flocking

In the flocking model, emergent behaviour is achieved by requiring all agents to adhere to the three rules, seperation, alignment and cohesion. By turning off the alignment and cohesion rules, the agents will only seperate from one another and therefore no emergence will result. Running the model in these two configurations allowed us to evaluate the effect of emergence on the constitutent agents. The number of agents reporting statistically significant correlations during simulations rose markedly when emergence was introduced to the model, from 10.1% without emergence to 37.8% with emergence. The model also demonstrates a large degree of fluctuation in the number of significant correlations reported, as illustrated in Figure 9, particularly in simulations with emergence where they range from 19.4% to 54%. It should also be noted that the maximum reported value without emergence is lower than the minimum value reported with emergence, although this result is unique to this model.

B. Segregation

The segregation model was run in two configurations. The first of these specified that agents require 90% of their neighbours to be the same colour as them to remain in the same position. No emergence occurred in this configuration. The second configuration specified a lower threshold of 75% of similarly coloured agents, generating compelling emergent ghetto patterns as illustrated in Figure 5.

This model demonstrates an increasing number of statistically significant correlations being reported over time when emergence is present in the model, as illustrated in Figure 10. This reflects the nature of the emergent phenomenon in the model, the formation of contiguous blocks of similarly coloured agents, and how these grow in size over time. This sees the number of statistically significant correlations rise from 13.8% to over 60% by the time the simulation has been completed.In comparison, a mean of 12.1% is observed throughout the simulation when no emergence is present, with little fluctuation occuring around this. It is noteworthy that the

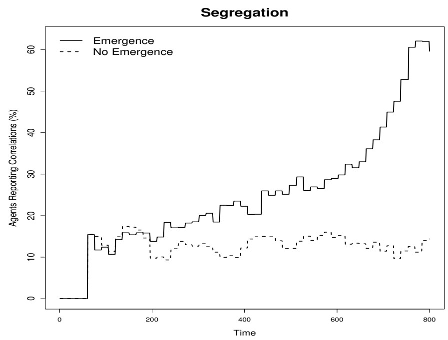

Fig. 10. Segregation Results

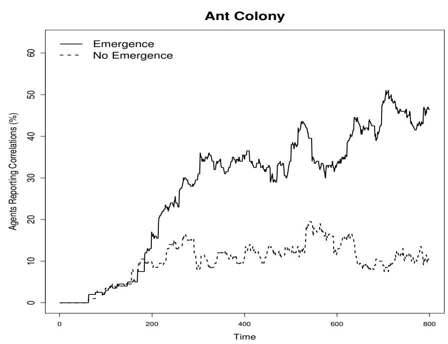

Fig. 11. Ant Colony Results

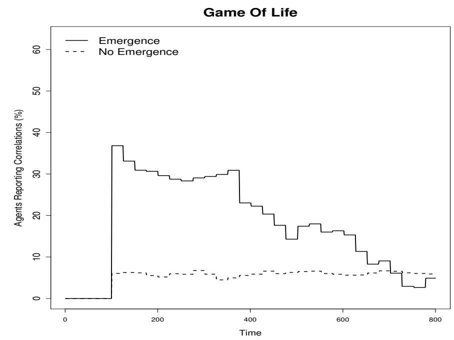

Fig. 12. Game Of Life Results

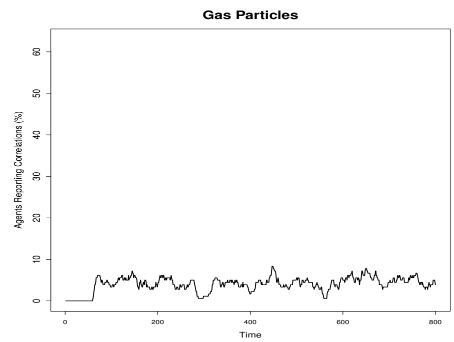

Fig. 13. Gas Particles Results

maximum level of no-emergence is greater than the minimum level of the with-emergence case. This implies that it is not a trivial task to find a threshold level of agents reporting such correlations, above which we can be confident emergence has occurred.

C. Ant Colony

The presence of food in the environment prompts the creation of emergent paths in the model. Therefore, the model was run with food, facilitating emergence, and without food to enable a comparison to be made between the two configurations. The presence of emergence in the Ant Colony model results in an increased number of agents reporting statistically significant correlations, with a mean of 35.5% throughout the simulation, compared to just 12.1% when there is no emergence present. However, the model can report a large number of such correlations even without emergence present with a maximum value of 19.5% reported. As illustrated in Figure 11, this peak, obtained at approximately timestep 550 does demonstrate some persistence and does not immediately dissipate back to the average. As with Segregation, this has the potential to complicate reaching a decision on the existence of emergence.

D. Game Of Life

By adjusting values of the variables A, B and C the appearance of patterns can be regulated in Game of Life. Using the traditional values of 2, 3 and 3 respectively [38] we found that the model generated the emergent phenomenon as expected. A non-emergent simulation was facilitated by adjusting these values with values of 6, 7 and 1 respectively.

The results for the model, illustrated in Figure 12, contrast with the results obtained for every other model as the number of agents reporting statistically significant correlations when emergence is present is initially large and gradually reduces over time. This sees the level of such reports, after our 200 timestep cut-off, drop from a maximum 30.9% to only 2.7%. This drop reflects the characteristics of the model, where the number of alive cells will fluctuate throughout a simulation and only alive cells will cause the state of other cells in the environment to change. As a result, when there are a relatively small number of alive cells present, large areas will remain dead for long periods. This feature of the model is demonstrated in Figure 7. However, when emergence is removed from the model, the level of agents reporting statistically significant correlations remains relatively constant around a mean of 6% throughout the simulation.

E. Gas Particles

The final model implemented does not generate emergent behaviour and so a single plot of results is included in Figure 13. As is the case with the other models, when emergence is absent, the number of reported statistically significant correlations is low across all agents. In this model, a mean of 4.3% of agents report such correlations throughout the simulation.

VII. Discussion

Emergence results in a downward causality or feedback from the macro-level of the system, where the emergent behaviour or property occurs, to the micro-level where the constitutent agents of the system reside and interact. We have presented experimental results demonstrating that the effect of this feedback can be detected by the constituent agents through the appearance of statistically significant correlations, in variables locally available to each agent. All models presented showed an increased number of agents detect such correlations when emergence was present, although the size of this increase, and the baseline level of correlations without emergence differed across models. Nonetheless, for each individual model, the difference between the correlations with and without emergence is significant, supporting the hypothesis outlined in the introduction. By showing that individual agents can detect this feedback by only observing their locality, these results provide a first known step towards facilitating decentralised detection of emergence.

We do not argue that an individual agent alone is capable of making an assertion about the global system and the presence of emergence by only observing its locality for the appearance of correlations. The use of P-Value, with a threshold of 0.05, to determine the statistical significance of a correlation between two variables means that we can reasonably expect 5% of results to be false positive when there is no statistically significant correlation present. Additionally, the properties of individual models may mean that significant correlations are detected at random times by certain agents without any feedback resulting from macro emergent phenomenon. This is apparent in our results with a baseline of 9% of agents reporting statistically significant correlations across all models even in the absense of emergence.

However, as the number of agents simultaneously experiencing the appearance of statistically significant correlations increases when emergence is present (from 9% to 30% on average) agents can work together to detect this increase and therefore indicate the presence of emergence. To achieve this detection in a fully decentralised manner requires a number of further steps that motivate our future work in this area.

The first of these steps addresses the limited observational range of individual agents and instead requires the agents to collaborate with one another to be able to aggregate their local experiences so that they can facilitate a sufficiently global observation. Emergent phenomena are global in their nature in that they are caused by and impact a large proportion of agents in the system. However, it is not always the case that they impact all agents in the system, and some agents will be sufficiently remote from the phenomenon that they do not experience any feedback from it. This relationship can be illustrated using the example of a traffic jam, (the emergent phenomenon) which causes a gridlock in the city centre. Traffic may move freely on the outskirts of the city meaning that only those agents (cars) local to the emergence are constrained by it. Enabling agents to find such boundaries so that they can detect emergence without requiring global consensus is a key component of this task. Our future work will focus on exploring methods to achieve this with distributed agreement protocols [28] [29] and ergodicity measures [30] providing initial points to explore.

Another challenge is presented by the dynamic nature of emergence. Emergence may appear, where none previously existed, when the system evolves and be persistent only for some period of time [6]. This characteristic is reflected in the constantly changing level of agents that report statistically signficiant correlations in our experiments, even when emergence is present in the models. This imposes a timing consideration on the detection of emergence, which can often be harmful to the constituent agents and should thus be detected promptly when it occurs. However, achieving this when the nature and scope of the emergence is itself dynamic is non-trivial.

Although we have demonstrated that detecting statistically signficiant correlations in the agents' locality can provide the foundation for a decentralised technique to detect emergence, additional work must be done to make such an approach model-independent. The variables we have selected for each model are specific to each, and were selected based on the characteristics of the particular model involved. This assumes a knowledge of the significant variables to monitor before the system components are deployed, and such knowledge is not reasonable in the case of CAS. Therefore, any distributed detection framework should provide agents with a way of learning the relevant indicator variables to monitor as the system evolves. Finally, the models we tested all exhibited different baseline levels of agents reporting statistically significant correlations when the system did not exhibit emergence, with different minimum and maximum values across the models. This suggests that agents should also be equipped with a means of learning this baseline in their own system and the detection of emergence will be based on departures from this normal level.

VIII. Conclusion

Emergence is a hallmark of complex adaptive systems. It arises unpredictably through the non-deterministic interactions of autonomous decentralised components and agents. These characteristics present a significant challenge as emergent behaviour can often be unwanted or harmful, to both the constituent components and the system as a whole. As a result, emergent behaviour and properties of a system should be detected by the system components when it occurs at run-time, through agent collaboration in the absence of any centralised controller or complete global system view.

In this paper, we have provided an important step towards this goal by demonstrating that individual agents can detect the impact of emergence in their locality. This impact is the result of the naturally occuring downward causation that results from the macro-level emergent properties, and acts to constrain the individual agents at the micro-level of the system. In a case study of 5 multi-agent systems, we demonstrated that this feedback results in statistically significant correlations being detected across agents simultaneously in locally available variables, where no correlations existed without emergence.

For future work, we will focus on incorportating the detection of downward causation into a decentralised framework enabling constituent agents to detect and reason about emergent phenomenon. Existing distributed agreement protocols and ergodicity measures can provide an initial starting point, however determining an efficient and practical boundary between what is local and what is global presents a key challenge. We will also examine ways to make our approach model independent, by exploring techniques to enable agents to discover and learn the important variables to monitor in their environment. Finally, the dynamic nature of CAS where properties and behaviour at both the micro-level and the macro-level are constantly fluctuating introduces a timeliness consideration that will also be addressed.

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