

## **Minimal Agents Utilise Global Dynamics During a Group Coordination Task**

### **Abstract**

Recent work has highlighted the importance of dynamic and embodied interaction during the performance of social tasks in minimal agents. Whilst informative, such work has focused solely on the interactions between two agents. As such, the question of how cognitive agents interact in groups has remained unanswered. The present study replicates and extends a simple model of social interaction in minimal agents to include a third agent. After evolving agents to remain coordinated in the presence of noise, we examined the effects of replacing one agent with a pre-recorded ‘dummy agent.’ Whilst the live agents remained robust to parameter values beyond those they were initially evolved to, the dummy agent caused the entire group’s performance to fail. These results offer a conceptual basis by which to suggest that social interaction in groups relies on the global dynamics of the various agents, such that the interaction process cannot be reduced to the information processing of a single individual.

### **Introduction**

Throughout cognitive science, computational theories have been a mainstay in the discussion of social cognition: the question of how humans think about others. A landmark study in this field was Trevarthen’s Double TV-Monitor Experiment (1985). In this paradigm, an infant interacts with its mother via a screen, such that both individuals can watch and react to one another. In a playback condition, however, the baby is shown prerecorded footage of the mother instead of a live feed. Despite there being no difference in the pattern of visual stimulation the baby receives, the infant tends to become distressed at viewing the prerecorded video. This was seen as evidence for the infant’s innate and internal ability to recognise agency in another individual (Russell, 1996; Gergely and Watson 1996). Indeed, subsequent studies suggested infants as young as two months possessed these capabilities (Nadel, 1999). Such interpretations, however, are far from ubiquitous. It seems unlikely, for example, that infants of this age possess such capacities considering that it is generally agreed that children do not possess a Theory of Mind (the ability to attribute mental states to other agents) until at least 15 months of age (Onishi and Baillargeon, 2005; Carruthers, 2013). In this way, it would seem that strict representational approaches to cognitive science have failed to provide convincing explanations of infants’ abilities to detect agency from as young as two months old and, as such, the question of whether computational frameworks can offer insight into social cognition has been called into question.

A dynamical approach to social interaction has utilised methods from the field of evolutionary robotics to simulate the Double TV-Monitor paradigm and provide alternative explanations of infants’ behaviour that do not rely on complex innate capacities. Froese and Di Paolo (2008) built on earlier work by Iizuka and Di Paolo (2007) to evolve two minimal agents that could discriminate live agents from pre-recorded ‘dummy’ agents. In both these studies, it was found that the co-regulation of the agents’ movements was essential to the maintenance of their interaction. Specifically, one agent utilised transient dynamics of the system whilst the other acted reactively, resulting in the time of contact being increased when they crossed paths and thus interaction being sustained (Iizuka and Di Paolo, 2007). One agent alone

could not perform this mutuality of interaction, and as such interaction dissipated when one agent could no longer act reactively to the other's behaviour. Such simulations have offered evidence for an enactivist theory of social interaction: individuals do not recognise agency in others via solely neural and internal processes but rather due to the ongoing dynamics of the embodied agents as they react to one another and their environment. Moreover, it is not our partner's actions alone that prompt the perception of agency, but *how that action relates to our own*. Seen in this way, the process of social interaction has been described as autonomous inasmuch as it emerges through the physical coupling of two bodies, such that the emergent dynamics influence the subsequent behaviour of the agents in a cyclical manner (De Jaegher and Di Paolo, 2007).

The notion of an autonomous interaction process that is irreducible to any individual within the social situation has yet to be explored beyond models involving only two agents. Indeed, a thorough understanding of social cognition in humans will be incomplete until the abilities of humans to interact in groups are accounted for in a convincing manner. Cognitivist explanations still center around the 'cognitions' and 'attributions' made by the individual regarding others (Blumberg *et. al*, 2012). One can grasp the nature of this staunchly computational account of social cognition in groups in the following excerpt from Pryor and Ostrom (1987):

*'...virtually all group processes are understandable through an analysis of how individual group members process group-relevant information.'*

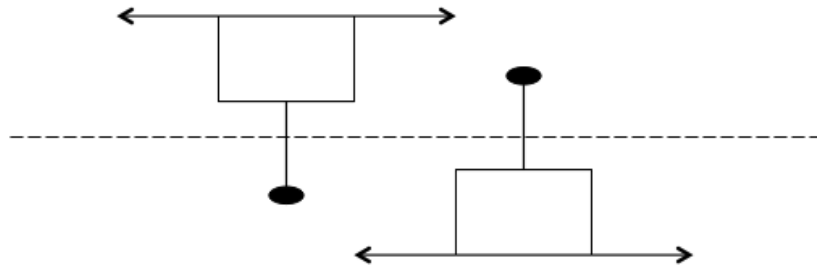
Such reduction to the individual is in conflict with the enactivist approach presented above, but it is yet to be directly challenged in reference to groups of agents. It is thus the role of the present study to investigate whether minimal agents in groups of three rely on the global dynamics of the group to maintain coordination, or whether such interactions can be reduced to the level of the individual.

To achieve this aim, we replicated and extended the model described by Froese and Di Paolo (2008). As reported in previous work, maintenance of interaction was found to require mutual reactivity in a system with two live agents. More notably, in a system with three agents, the replacement of one of those agents with a non-reactive dummy caused the interaction of *all three* agents to deteriorate, confirming our hypothesis that social interaction in groups relies, at least in part, on the global dynamics of the group and cannot be sustained when a member of that group can no longer interact dynamically with others.

## Methods

### *Task One*

We first replicated the minimal simulation of Murray and Trevarthen's (1985) experiment described by Froese and Di Paolo (2008). In this model, two agents are set facing each other in a continuous one-dimensional space. The agents have a sensor at their centre and are only allowed to move in a horizontal direction. This set up is illustrated in Figure 1.



**Figure 1.** Two agents face each other in one-dimensional space. They can only move horizontally and are able to sense each other using the sensor attached to their bodies. The agents are 40 arbitrary units of space wide.

The agents are evolved to cross paths with one another as far away from their starting point as possible. A ‘cross’ is defined as any point wherein the two agents are within 40 arbitrary units of space from one another. This task is non-trivial since an agent’s sensor conveys neither the direction nor the speed of the other agent’s movement. Furthermore, since the agents are facing each other, the genetic algorithm cannot produce a simple solution to the problem, such as moving both agents in the same direction as quickly as possible.

In alignment with Froese and Di Paolo’s (2008) simulation, two identical continuous time recurrent neural networks (CTRNNs) were used as agents. The agents detect each other using the sensor at their centre. When the opposite agent is directly facing them, they receive a sensory input of 1. As the distance between the two agents increases to 200 arbitrary units of space, the sensory stimulation decreases continuously to 0. In the dummy condition, pre-recorded movements of Agent Two were used, such that Agent One could still detect and react to the dummy’s location, whilst the dummy’s movement remained unaffected by that of the live agent.

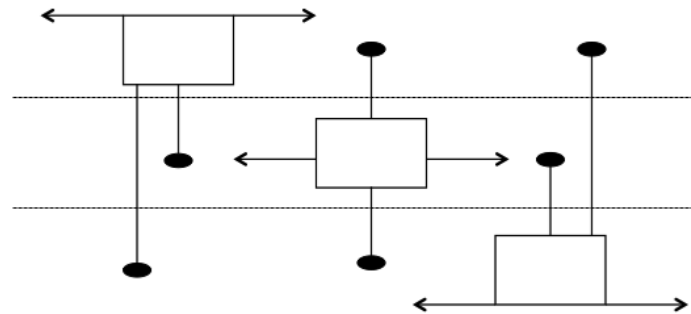
Since the agents are identical, noise must be introduced in order to prevent their movements being indistinguishable. As such, both motor and sensory noise was added to the simulation. At each Euler time step, there was a 30% chance that the agent’s sensory input would be changed to 0, regardless of its current state. Noise drawn from a normal distribution ( $\mu = 0, s^2 = 0.5$ ) was also added to the motor outputs of each agent.

The agents have their initial relative displacement varied in the range of -25 to 25, with Agent Two always beginning at 0. From this position, the agents must cross locations as far away from 0 as possible to maximise their fitness.

### *Task Two*

Task One was subsequently adapted to include the presence of a third agent. The agents remain in a one-dimensional space, only moving horizontally. It makes less sense to describe the agents in terms of the direction they ‘faced’ in this scenario. This is because, whilst one of the agent’s velocities must be negative to move in the same direction as the other two agent’s velocity (the method by which the direction being faced was modelled in Task One), the agent with the negative velocity can still detect

the presence of both other agents above and beneath it. In any case, the evolutionary algorithm is still prevented from hardcoding a simple solution for the same reasons as in Task One. This is clarified in Figure 2.



**Figure 2.** Three agents interact in a one-dimensional space. Each individual can only move horizontally. The agents detect one another through agent-specific sensors attached to their bodies. The middle agent, Agent Two, begins each trial at a location of 0.

The goal of the agents continues to be to cross each other's paths as far from the starting location as possible. It should be noted, however, that in this task a crossing point is only recorded when *all* the agents are within a range of 40 units of space from one another. Furthermore, the agents now have sensors dedicated to the detection of each of the other agents, such that they have two sensors each. The sensors work in the same way as in Task One, receiving an input of 1 when a neighbouring agent is directly in front of them and receiving a continuously diminishing input as the neighbour moves 200 units of space away, at which point input becomes 0. Agent Two continues to start each trial at 0, whilst Agent One and Three start in the same location as each other, with their starting points varied once again in a range of -25 to 25. The same levels of noise were added to the simulation as those chosen in Task One.

Once again, movements of Agent Two were recorded for use as a dummy in the dummy condition, such that Agents One and Three could still respond to its predetermined movements without the dummy being affected by their activity.

### Agents

The CTRNNs controlling the agents consist of 3 fully connected nodes with self-connections. The network is defined such that, over time, the activation of the nodes is described by the following equation:

$$\frac{dy_i}{dt} = -y_i + \tanh \left[ \sum_{j=1}^N w_{ij} y_j + I_i \right]$$

In this equation, the nodes of the CTRNN are denoted by the variable  $y$ ,  $N$  refers to the number of nodes in the network and  $w_{ij}$  describes the strength of connection from node  $i$  to node  $j$ .  $I$  is the input to each node in the network. Here, we use a simple hyperbolic tangent function as the transfer function. In Task One, all nodes receive sensory input. In Task Two, there is a dedicated sensory node for the detection of

each other agent, leaving one node without sensory input. Sensory input is calculated by mapping the distance between two agents to values between 1 and 0 (corresponding to relative displacements of 0 and 200, respectively) and then multiplying it by a sensor gain in the range of 1 to 100. Two of the agent's nodes are used to calculate motor output: one node controls rightward velocity whilst the other controls leftward velocity. The agents overall direction is calculated simply by multiplying the value at each motor node by an individual gain parameter (in the range of 1 to 50) and then finding the difference between them. The agent's activity over time is integrated numerically using Euler integration and an Euler time step of 0.05.

Whilst the present study intended to replicate and extend the work of Froese and Di Paolo (2008), there are several important differences in methodology. Firstly, we used an alternate equation to determine CTRNN activity. Second, Froese and Di Paolo utilised binary on/off sensing in their model, whereas the present simulation makes use of continuous values in the range of 0 to 1. Both these adjustments increased the evolvability of the agents without altering the conceptual basis for the study and were therefore deemed acceptable modifications to the original work.

### *Genetic Algorithm*

The present study evolved the CTRNNs using a simple microbial genetic algorithm (GA) (Harvey, 2009). Until the maximum number of tournaments is reached, two individuals situated close to one another (a deme size of 3) in a population of 40 are selected and have their fitness compared. The agent with the highest fitness has their fitness re-evaluated and is then returned to the population. The loser undergoes recombination with the winner as well as mutations before it has its fitness evaluated and is placed back in the population. This process comprises one tournament. The algorithm consisted of 5000 tournaments.

Crossing over occurs with a probability of 0.5, whilst the probability that a particular gene is mutated is:

$$\frac{1}{\text{Number of Genes}}$$

which equated to 0.083 in our model. Creep mutation was implemented such that any gene would be mutated by multiplying a random value, drawn from a normal distribution ( $\mu = 0, s^2 = 1$ ), with the range of the parameter divided by a factor of 100. If a mutated gene exceeded the parameter's maximum limit, the value would return at the lower limit, and vice versa.

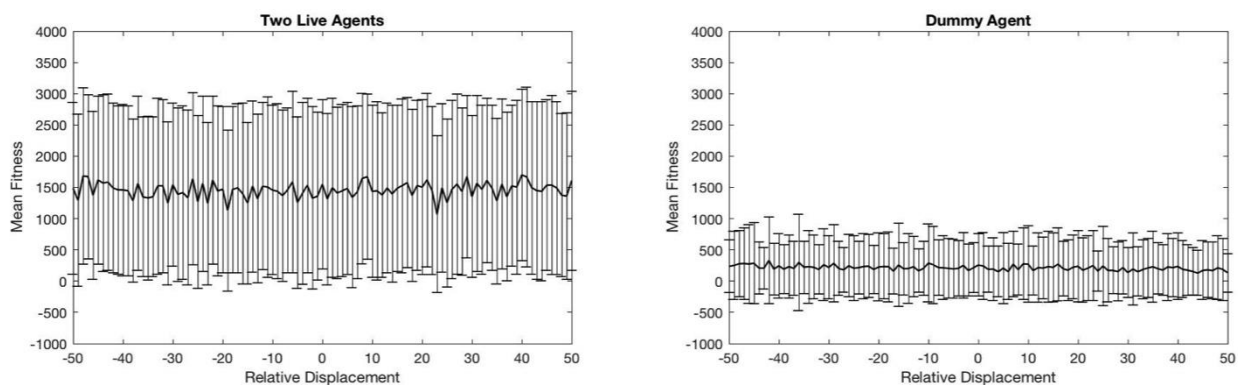
Fitness of an agent was established over 15 trials. The final fitness for each evaluation was recorded as the median of the 15 trials to prevent atypical trial runs obscuring the evolution process. The agent's initial activations were randomly set from a normal distribution at the start of each trial whilst the noise differed across every trial. When evolving agents for Task One, Agent One started from 15 linearly spaced positions in the range of -25 to 25, whilst Agent Two always started from 0. Likewise when evolving agents for Task Two, Agent One and Three started from the same 15 positions, with Agent Two beginning from 0. Each trial run was 500 Euler time steps long and resulted in a single fitness score. The fitness score in Task One is simply the

absolute value of the final crossing position of the two agents. In Task Two, it is the final crossing point of *all three* agents.

## Results

### Task One

After running the GA for Task One, the fittest agent of the final population was tested. Agent Two always started from position 0, whilst Agent One started from 101 linearly spaced positions in the range of -50 to 50, thus increasing the relative displacements of the two agents on which the controllers were initially evolved. Every trial was repeated 150 times. The movement of Agent Two on the highest scoring trial was recorded and used as a Dummy Agent in a repeat of the process. The mean of each trial is displayed in Figure 3. There was a significant difference in the overall mean between the live condition ( $M = 1459.20$ ,  $SD = 1482.62$ ) and the dummy condition ( $M = 213.78$ ,  $SD = 504.21$ ),  $t(200) = 97.28$ ,  $p < .0001$ .

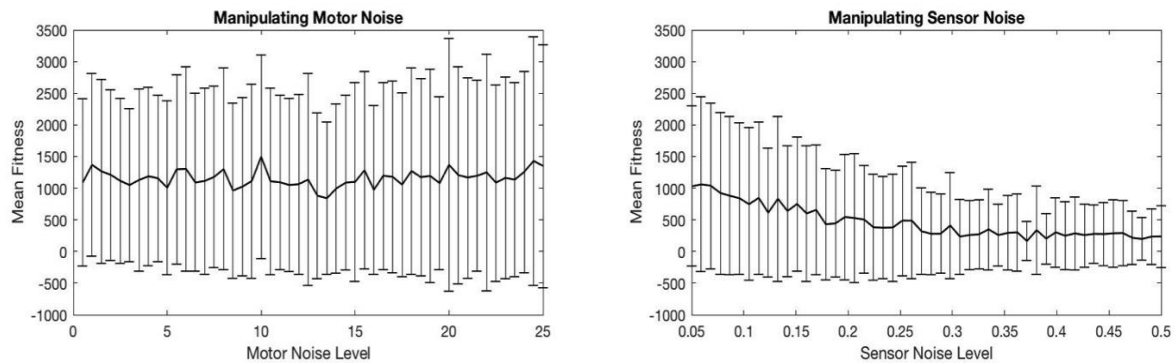


**Figure 3.** Left: The mean scores achieved following 150 trials on 101 different starting locations when both agents could react to one another's movements. Performance is robust to the increased range of relative displacements. Right: The mean scores achieved when Agent Two is replaced with a Dummy Agent. Error bars illustrate standard deviations.

To examine whether performance was robust to variations in noise, the noise level was varied as the agents performed 150 trials with both agents starting from 0. Whilst testing variations in motor noise, sensory noise was held at the evolutionary level and vice versa. Results from these tests are displayed in Figure 4. One can see that they are resilient to changes in motor noise and undergo graceful degradation as sensor noise level is increased, indicating that the agents could maintain robust interactive behaviour in the presence of noise.

A final experiment was performed to investigate the difference between the live condition and the dummy agent condition. Both agents were started at 0 for 150 trials and the mean performance was taken. Agent Two's movements on the highest scoring trial (score: 3982.80) was recorded for use as the Dummy Agent in the Dummy condition. There was a significant difference in performance between the Live agent ( $M = 1507.64$ ,  $SD = 1976.41$ ) and Dummy agent ( $M = 649.19$ ,  $SD = 1297.97$ ) conditions,  $t(298) = 4.1875$ ,  $p < .0001$ . This highlights the necessity of mutual, coupled dynamics to maintain coordinated interactions in minimal agents.

Figure 5 displays the agents' movements in the highest scoring run from the Live Agents condition next to a typical run from the Dummy Agent condition.



**Figure 4.** Left: As motor noise is increased from a variance of 0.05 to 25, performance of the agents remains relatively constant across 150 trials. Right: As sensor noise increases from a probability of 0.05 to 0.5, performance declines gracefully to the level of performance with a dummy agent. Error bars depict standard deviations.

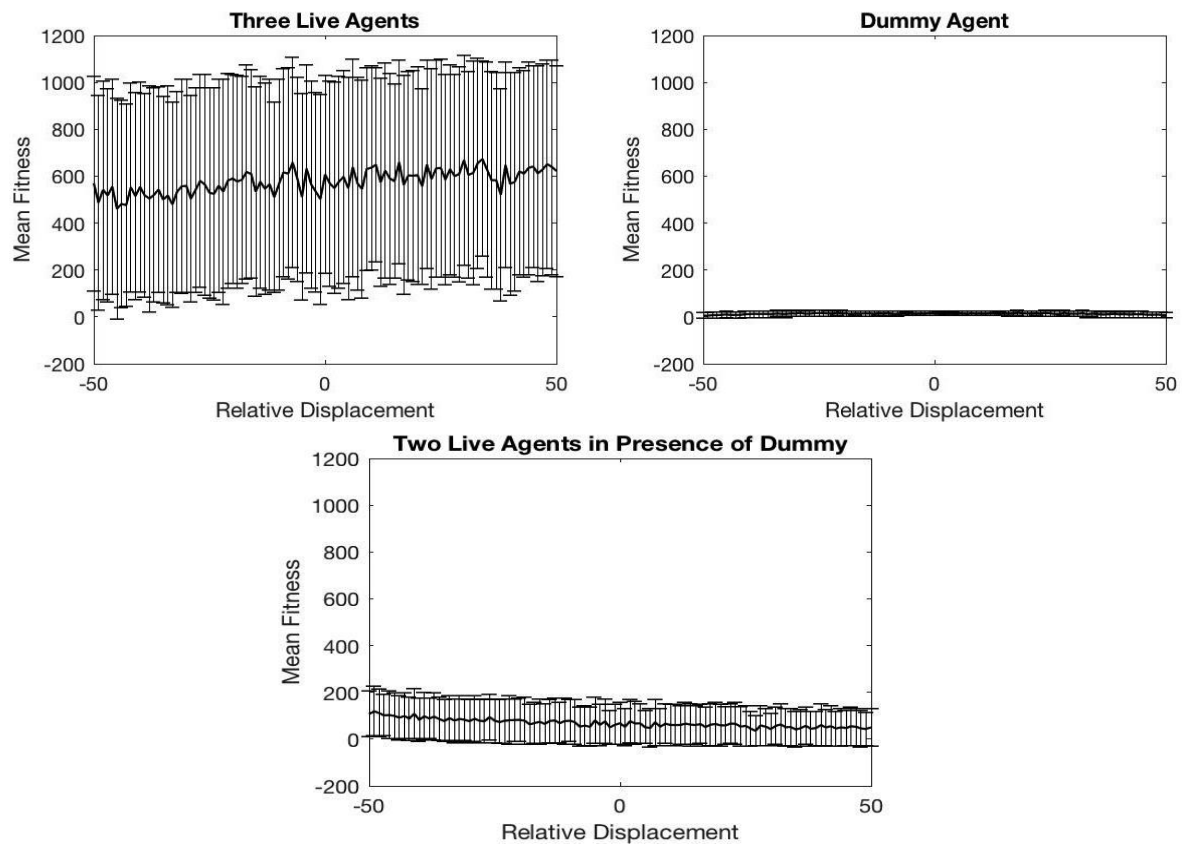


**Figure 5.** Left: The movement of the two agents during the highest scoring trial in the Live Agent condition. Right: A typical run when the Dummy Agent cannot interact dynamically with Agent One.

### Task Two

The GA for Task Two was run and the fittest individual in the final population was selected for testing. Agent One and Three started from 101 linearly spaced points in the range of -50 to 50, doubling the relative displacement from Agent Two on which they were evolved. The agents underwent 150 trials at each starting location and the mean was taken from each. Movement of Agent Two on the highest scoring trial was recorded and used as the Dummy Agent in the dummy condition. These results are illustrated in Figure 6. Performance in the live condition ( $M = 577.70$ ,  $SD = 445.21$ ) was significantly better than the dummy condition ( $M = 13.21$ ,  $SD = 5.81$ ),  $t(200) = 114.54$ ,  $p < .0001$ . Moreover, performance in the live condition was significantly better than performance of the two live agents in the presence of the

dummy (where only the cross locations of the live agents were recorded as a measure of success) ( $M = 50$ ,  $SD = 87.21$ ),  $t(200) = 101.00$ ,  $p < .0001$ .

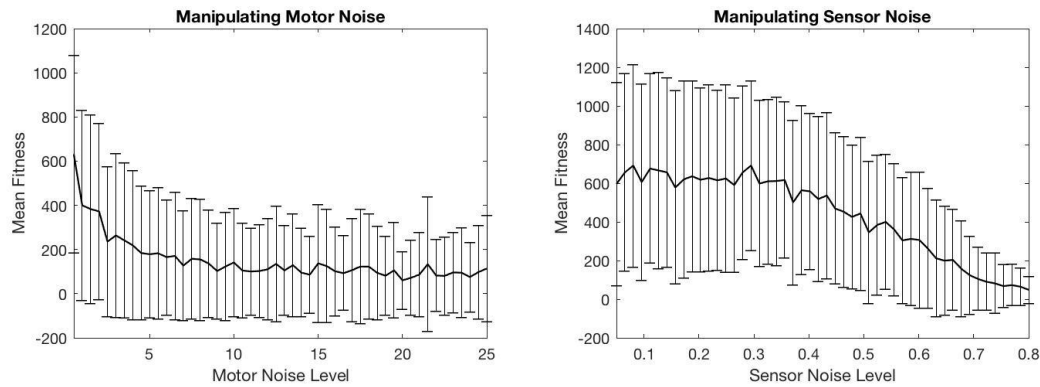


**Figure 6.** Top Left: The performance of agents is robust to increasing their relative displacement beyond that on which they were evolved. Top Right: The agents completely fail to succeed in the task when they are in the presence of one Dummy Agent. Bottom: The two live agents failed to reach the performance of the agents when all three were live.

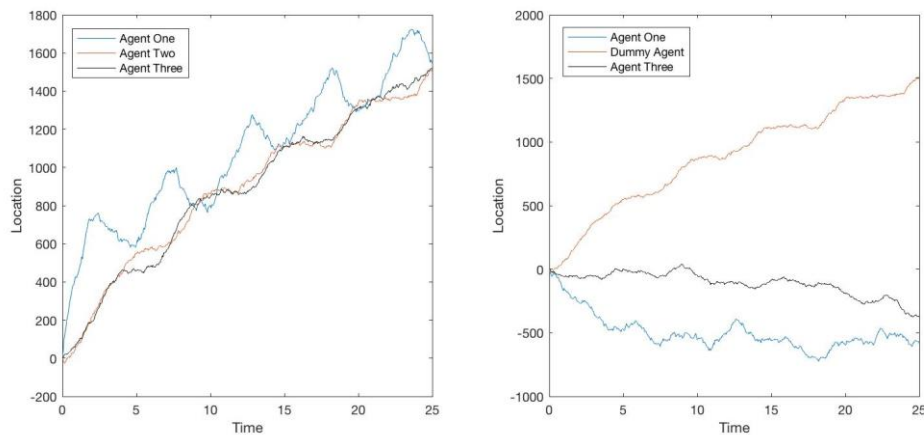
Once again, we tested whether the evolved solution would be robust to noise and indeed this was found to be the case. As motor noise and sensory noise were increased independently, the performance of agents in the live condition degraded gracefully. This can be seen in Figure 7.

We performed one final experiment with all agents starting from 0. The mean performance was recorded over 150 trials with Agent Two's movements in the highest scoring trial (Score: 1506.47) recorded for use as the Dummy in the dummy condition. Three live agents performed significantly better ( $M = 606.56$ ,  $SD = 441.40$ ) than when a dummy was present ( $M = 88.19$ ,  $SD = 271.22$ ),  $t(298) = 12.25$ ,  $p < .0001$ . This suggests that global dynamics are required to maintain coordinated interaction in a group of agents. Finally, the coordinated behaviour produced by three live agents can be seen in Figure 8 alongside the failure to interact when one agent is replaced with a dummy.





**Figure 7.** Left: As motor noise is increased from a variance of 0.05 to 25, performance of the agents remains relatively constant across 150 trials. Right: As sensor noise increases from a probability of 0.05 to 0.5, performance declines gracefully to the level of performance with a dummy agent. Error bars depict standard deviations.



**Figure 8.** Left: The live agents' locations on the highest scoring trial in the final experiment of Task Two. They remain coordinated as they move through time. Right: When one agent is replaced with a dummy, none of the agents are able to coordinate behaviour successfully, leading to an entirely unsuccessful trial.

### Discussion

The present simulation replicated previous results that underscored the importance of ongoing, dynamic interactions between two minimal agents (Iizuka and Di Paolo, 2007; Froese and Di Paolo, 2008; Froese and Fuchs, 2012). In addition to this, it was found that, in a scenario with three agents, the interaction dynamics across all agents within the group was fundamental to the successful performance of a coordination task. Specifically, when one agent was replaced by a non-reactive dummy agent, the group's performance plummeted such that even the two remaining live agents could no longer coordinate effectively. The import of this result is highlighted when considering the fact that the group performance is resilient to significant noise increases as well as an enlarged range of starting locations. Despite this, performance is dismal in response to a dummy agent, even when that dummy agent replicates the movements of a high-scoring live agent.

Our results thus offer an alternative explanation to the cognitivist postulations of representations and simulations whilst describing social cognition in groups. It seems that the physical, embodied interactions individuals make with each other in a group are not merely expressions of successful social interaction but are a *necessary and constitutive* component of the interaction itself. Indeed, a complete description of the processes underlying group cognition cannot be found in reference to the internal processes of any one individual within that group, but rather by studying the global dynamics of the group as a whole, taking into account the actions of each agent and the subsequent reactions of every other agent at each point in time. In this way, the interaction itself takes on a distinct identity to that of the individual and itself becomes autonomous (De Jaegher and Di Paolo, 2007). It is not hard to imagine how these conclusions may be used to explain phenomena regularly experienced in group situations. For example, when the ‘atmosphere’ in a room becomes negative, it is often beyond the will of the individuals to help recover a relaxed dynamic throughout the group. In this way, the autonomy of the individual has become distinct from that of the social interaction itself, and the novel findings of this study suggest this social interaction is built from the dynamical reactivity of the embodied individuals, rather than anything internal to them.

Further work is still essential in order to confirm this hypothesis, however. The support for a dynamical account of social interaction has emerged through numerous studies investigating the specific dynamical methods used by minimal agents to distinguish between live and dummy agent, using either the paradigm utilised in the present study or ‘perceptual crossing’ experiments (Di Paolo *et al.*, 2007). For example, in the original simulation upon which this paper is based, it was found that one agent could not prevent its motor system falling into an attractor without the reactive help of its partner (Froese and Di Paolo, 2008). In this way, strict mathematical terms were used to specifically identify the dynamic interaction as being responsible for successful performance during the task. It is a shortcoming of the present study that such analysis was not performed; whilst Figures 5 and 8 offer some insight into the coordination tactics used by agents, such information is limited in its ability to uncover the exact reasons why the presence of a dummy agent proved insurmountable when attempting to maintain group interaction. As such, further work should analyse these group interactions formally according to dynamical systems theory. Indeed, such work undertaken in two agent models has proved successful, allowing even for a thorough explanation of the phenomenology of social interaction by reference to an ‘extended body’ (Froese and Fuchs, 2012). It is now essential for such research to focus on poly-agent models in order to build on the novel findings reported in this paper and to strengthen the arguments against an internalist view of social cognition in groups.

Moreover, it is important to restate the limitations of using so-called neural networks to draw conclusions as to the nature of human cognition; the parallels between a three-node network and the human brain are minimal. It is not the purpose of this paper to claim that the simulation performed utilises the same methods during interactions as humans. Rather, by explicating a model in which agents are able to perform non-trivial social tasks without any method of internal representation, we have provided a conceptual basis for alternative explanations of social cognition in groups that do not rest on the tenets of methodological individualism. This work thus

allows for future work to examine such explanations in empirical cases involving human participants, wherein firmer conclusions can be drawn regarding the nature of human cognition.

In sum, we have replicated and extended previous work relating to the social interactions of minimal agents. Specifically, the ability for three agents to remain coordinated in the presence of noise was found to rely on the global group dynamics, such that the removal of one live agent with a non-reactive dummy agent prevented any form of coordination amongst the group. As such, tentative evidence has been provided to suggest that social cognition in groups relies on the interactive dynamics of embodied agents, giving rise to a global and autonomous social interaction that cannot be reduced to any one individual within the group.

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