# Adaptability and Diversity in Simulated Turn-taking Behaviour

Hiroyuki Iizuka Takashi Ikegami

Department of General Systems Sciences,
The Graduate School of Arts and Sciences, University of Tokyo,
3-8-1 Komaba, Tokyo 153-8902, Japan

**Abstract**

Turn-taking behaviour is simulated in a coupled agents system. Each agent is modelled as a mobile robot with two wheels. A recurrent neural network is used to produce the motor outputs and to hold the internal dynamics. Agents are developed to take turns on a two-dimensional arena by causing the network structures to evolve.

Turn-taking is established using either regular or chaotic behaviour of the agents. It is found that chaotic turn-takers are more sensitive to the adaptive inputs from the other agent. Conversely, regular turn-takers are comparatively robust against noisy inputs, owing to their restricted dynamics. From many observations, including turn-taking with virtual agents, we claim that there is a complementary relationship between robustness and adaptability. Furthermore, by investigating the recoupling of agents from different GA generations, we report the emergence of a new turn-taking behaviour. Potential for synthesizing a new form of motion is another characteristic of chaotic turn-takers.

**Keywords:** turn-taking, adaptive behavior, diversity of behaviors, cognition, embodiment

## 1 Introduction

Dynamical systems can theoretically simulate behaviour produced over time with interactions between various entities. This approach, based on embodied cognition [12, 14, 15], has a different perspective from the traditional AI approaches. That is, representations are not given as symbols in advance but are only realized, by the dynamics, over time [1, 16, 20]. Cognitive structure is characterized by geometrical and flow patterns in an adequate phase space. As well as being characterized by attractor types (e.g., fixed point, limit-cycle, and strange attractors) they are also characterized by chaotic itinerancy and other novel concepts, such as open-ended evolution/dynamics, that describe their inherent behaviour.

Richness and the potential of the dynamical systems approach encourage us to go beyond merely adaptive behaviour. The higher functions, such as intention, motivation, emotion and consciousness, are within the scope of this study. Grey Walter has started the discussion of emotional, or play-like, behaviour by synthesizing artificial creatures [23, 24]. A wheeled vehicle containing a simple electric circuit can show unexpected and complex behaviour, comparable to that of living creatures. Without making real robots, Braitenberg made conceptual robots to discuss the higher functions [2]. In his thought experiments, he designed vehicles using simple hard-wired electrical connections from sensory inputs to motor outputs. His vehicles gradually showed more complex cognitive behaviours by providing more complex internal structures. For example, the most primitive behaviour is a sense of “aggression”, which is simply given by attraction to a light source with a crossed sensory–motor connection. However, to simulate more complex behaviour, such as association and concept formation, he has to implement new wires, such as mnemotorix and ergotorix wires, with some Darwinian-type selections. Grey Walter and Braitenberg have one thing in common, in claiming that any apparently complex cognitive behaviour can be built up from simple sensory–motor coordination. That is, agents can be cognitive by having physical constraints. We basically agree that any meaningful cognition should be embodied, but focus on different aspects.

In this paper, we focus on the cognitive behaviours of turn-taking and imitation, caused by interactions between two or more humans, in which it is thought that the sharing of mental states and intentions with others is important. There are many ways to understand psychological phenomena by computer simulations and robot experiments rather than by studying human behaviour directly [4, 5, 18]. We conducted computer simulations of two agents with internal dynamics, which were implemented by an artificial recurrent neural network, as a model of turn-taking behaviour. In our previous works, cognitive behaviours were explained from the dynamical systems perspective by coupling between agents with rich internal dynamics [8, 9, 10]. Here, we generalize from turn-taking behaviour to autonomous role-changing, such as games of tag among children, and investigate the generic underlying mechanisms using the dynamical systems method. Therefore, this study focuses on different perspectives from those of fixed role-playing games (e.g., a pursuit-evasion game [3]). Here we take turn-taking as the simplest example that shows the diversity of dynamics. For turn-taking behaviour, it is necessary for roles to be exchanged autonomously, within a context constructed by the entities' behaviours, e.g., chaser–evader and speaker–listener. When taking turns in a two-person conversation, people usually avoid overlapping or interrupting each other's speech without setting some explicit cue to switch speakers. Some cues for this include eye contact and the detection of intonation changes. It is considered that turn-taking is established by coordination between predictions and the internal neural networks that compute the output from the inputs. Therefore, coupling between agents means a coupling of anticipatory systems with intrinsic dynamics.

By introducing neural architecture, evolutionary algorithm and a turn-taking game in §2 and 3, we explore four topics in the simulation. The first topic is dynamic repertoire. We describe how turn-taking is established with different forms of motion. In particular, we argue in §4.1 that regular motion behaviour evolves into chaotic behaviour. The second topic is predictability. Each agent has to predict the other's future behaviour one step ahead. Interestingly, prediction precision decreases when the turn-taking role switches from one to the other. This will be discussed in §4.2. The third topic is ongoingness of interactions. Agents become robust against sensor noise; however, the turn-taking performance is established only when agents synchronize their dynamics precisely. This point is discussed in §4.3. The last topic is adaptability. As discussed in the section on dynamic repertoire, the turn-taking pattern appears to be different for different evolutionary generations. In section §4.4, we investigate the emergence of new spatio-temporal patterns by coupling agents from different generations. In §5, we discuss the potential linkage between these simulation results and the psychological experiments conducted by C. Trevarthen [22]. A concept of intersubjectivity is also discussed.

# 2 The Model

We modelled the playing of a tag game in which the role of chaser, or evader, is not given to players in advance. There are some game models in which the roles are not predefined. Reynolds also showed that the abilities of chasing and evading evolve simultaneously by genetic programming in a game of tag, which is a symmetrical pursuit-evasion game [17]. The variety in the behaviour of agents adapting to their environments is worth noting. In Reynolds' game, switching between evader and chaser is predefined as happening when both agents come into physical contact. The difference between Reynolds' model and ours is the spontaneous emergence of behaviour. Whether an agent plays the role of a chaser or an evader is dynamically determined in our model. On the other hand, Di Paolo modelled and studied social coordination with agents interacting acoustically [6]. To avoid misperceiving the acoustical signals, their emission timings were entrained in an anti-phase state; the resulting behaviour resembles a turn-taking process.

There is a difference between Di Paolo's turn-taking and ours. Both turn-taking behaviours are established by the coordination of agents through the history of their interactions. Di Paolo modelled turn-taking as the result of anti-phase signals to avoid signal interference; however, we modelled turn-taking behaviour as a result of coupling between richer internal dynamics. Therefore, in this paper, we pay more attention to the diversity of behaviour patterns.

## 2.1 Game and Environment

Here each agent has a circular body of radius R, with two diametrically opposed motors (Fig. 1). The motors can move the agent backwards and forwards in a two-dimensional unstructured and unlimited arena. The motion is described by the following equation of motion in terms of an agent's heading angle ($\theta$) and its speed ($v$) in that direction.

$$M\dot{v} + D_1 v + f_1 + f_2 = 0, \tag{1}$$

$$I\ddot{\theta} + D_2\dot{\theta} + \tau(f_1, f_2) = 0, \tag{2}$$

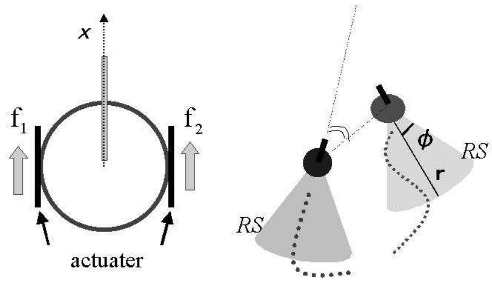


Figure 1: Left: a schematic view of the mobile robot with two wheels (actuators). It computes the forward force vector and the torque strength from the force vector $(f_1, f_2)$ on each actuator. Right: Two mobile robots interact to perform turn-taking behaviour by sensing each other's position, relative distance and heading angle. It is robot A's turn when A enters the area that is B's rear side (RS) position. The shape of this RS is parameterized by $r$ and $\phi$.

where $f_1$ and $f_2$ are the forward driving force, and $\tau$ denotes the torque. $D_1$ and $D_2$ express the resistance coefficients, and the agents have mass ($M$) and inertia ($I$). We solve the equations iteratively using the Runge–Kutta method. At each time step, the agents compute the forces from the inputs using the internal neural nets described below.

We assume there is no collision between agents because we focus on the internal states of the agents that generate turn-taking. Two agents try to coordinate their turn-taking behaviour, each trying to get behind the other. Because they cannot get behind each other simultaneously, the turn-taking cannot be achieved if both agents play chaser. Naturally, mutual turn-taking cannot be achieved if both agents play evader either. Therefore, it is necessary to have spontaneous symmetry break down so that one plays the role of chaser and the other plays the role of evader. However, mere symmetry breakdown is insufficient: temporal role changing is also required. By using recurrent neural networks, we focus on how the turn-taking dynamics are self-organized.

## 2.2 Agent Design

We designed the agents to have recurrent neural networks (Fig. 2). Inputs to an agent are the other agent's position, distance and heading angle, relative to the agent. Agents move freely in the arena using two motors, the outputs of which are computed at every time step of the game. Each agent predicts the other's next relative position, which is assigned to three output neurons. The dynamics of the recurrent neural network are expressed by the following equations at each time step $t$,

$$h_j(t) = g(\sum_i w_{ij} y_i(t) + \sum_l w'_{lj} c_l(t-1) + b_{j1}), \tag{3}$$

$$z_k(t) = g(\sum_j u_{jk} h_j(t) + b_{j2}), \tag{4}$$

$$c_l(t) = g(\sum_l u'_{jl} h_j(t) + b_{j3}), \tag{5}$$

$$g(x) = 1/(1 + \exp(-x)), \tag{6}$$

where $y_i, z_k, h_j$ and $c_l$ represent input, output, hidden and context nodes, respectively. The respective number of nodes in these layers is set to $(I, K, J, L) = (3, 5, 10, 3)$ throughout this paper. The symbols $w_{ij}, u_{jk}, w'_{lj}$ and $u'_{jl}$ denote the weights from input to hidden, hidden to output, context to hidden, and hidden to context neurons, respectively, and the parameter $b$ is a bias node. In this paper, we do not consider the results of predictions, which are discussed in [11]. This network architecture evolves using a genetic algorithm as explained in the following section.

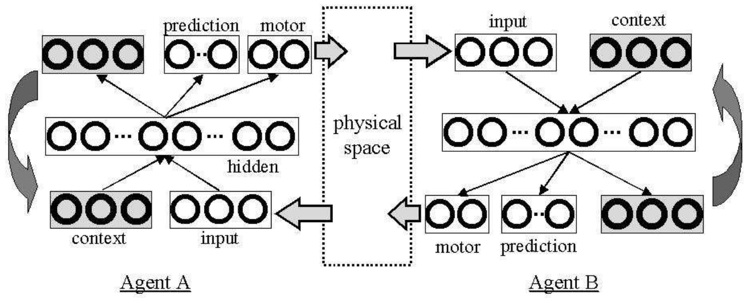


Figure 2: Recurrent neural networks with three layers. Input nodes receive the other agent's relative position. The final layer consists of three types of node: context, prediction and motor output. Context nodes feed back to the input layer. Prediction nodes output the other's relative position in the next time step. Motor nodes output the force vector, $f_1$ and $f_2$.

# 3 Genetic Algorithm and Noisy Environment

## 3.1 Genetic Algorithm

We update the weights according to the turn-taking performance. In practice, the weight set of the neural networks has a vector representation of the real weight values, which evolve using a genetic algorithm (GA).

We use a GA to evolve two separate populations, to avoid agents of a single genotype from dominating, in which case turn-taking is played between genetically similar agents. As a result, a player has to play against itself, which we wish to avoid. Each population contains $P$ individuals. The performance of all $P^2$ paired agents from the separated populations are evaluated at each generation. Agents that can exchange turns equally are evaluated as having greater fitness. At first, individuals in each population are initialized with random weight values. Then we calculate the fitness of each individual, based on its performance.

The highest value is given when both agents take their turn alternately and the agents can predict each other's behaviour. A one-sided (i.e., role-fixed) behaviour is associated with lower fitness values. Practically, the fitness of an agent $\boldsymbol{a}$ from a population ($A$) against an agent $\boldsymbol{b}$ from the other population ($B$) is calculated as follows. Below, we define a total fitness $F$ as the sum of two fitnesses associated with prediction and turn-taking, respectively. When one agent gets behind the other, by definition the other agent has its turn and the rear scope is specified as $RS$, which is parameterized by two parameters $r$ and $\phi$ (see Fig. 1). The agent in this state is said to be having its turn and is rewarded. A spatial position of agent $\boldsymbol{b}$ at time step t is represented by $Pos_b(t)$. This is compared with agent $\boldsymbol{a}$'s prediction value $Pos_{a\to b}$. Therefore the squared difference (Eq.(11)) is the measure of the precision of agent $\boldsymbol{a}$'s prediction.

$$
\begin{aligned}
F_a &= \frac{1}{P}\sum^{P}\left(s_1 \times F_a^{turn} + s_2 \times F_a^{predict}\right), && (7)\\
F_a^{turn} &= \sum_t^T g_a(t) \times \sum_t^T g_b(t), && (8)\\
g_a(t) &= \left\{\begin{array}{ll} 1 & Pos_a(t) \in RS_b(t) \\ 0 & Pos_a(t) \notin RS_b(t) \end{array}\right\}, && (9)\\
F_a^{predict} &= -\sum_t^T P_a(t) \times \sum_t^T P_b(t), && (10)\\
P_a(t) &= (Pos_b(t) - Pos_{a\to b}(t))^2. && (11)
\end{aligned}
$$

The performance of turn-taking is evaluated for different lengths of time ($T = 500, 1,000$ and $1,500$), so that agents cannot tell when the evaluation time is over. Evaluating the turn-taking performance at each GA generation, we leave the best $E$ individuals in each population and let them reproduce with specified mutation rates. The GA proceeds by repeating this procedure, and the recurrent neural networks evolve.
In addition, the following points should be noted.

### 3.2 Two Time Scales

Two time scales exist: the vehicle navigation time scale ($\Delta T_1$), and the neural computation time scale ($\Delta T_2$). The time evolution of the vehicle navigation is computed using the 4th order Runge-Kutta method, where $\Delta T_1$ is set to 0.01. The basic process is that the neural net receives the sensor inputs and computes the motor outputs. By assuming that the vehicle navigation motion is faster than the internal neural time scale, we take $100\Delta T_1 = \Delta T_2$. For simplicity, the neural net produces the outputs every 100 Runge–Kutta time steps. When the network structure evolves by GA, the time scale ratio is implicitly reflected in the net structure. Therefore, we believe that the same behaviour structure can be obtained, at least qualitatively, for a different scale ratio.

### 3.3 Noisy Environment

Living systems are involved in a fundamentally noisy environment. We know that our perception has to deal with noisy inputs. However, it is not possible to discriminate noise from other signals. We, as living systems, behave adaptively, cooperatively or selfishly while handling the problem. Therefore, we simulated the agents' interacting with each other in a noisy environment. Noises are added to the input neurons at every game step during each run in the GA. The strength of noise is provided by uniform random numbers between zero and almost the maximum distance the agent can move during one game step. In the next sections, spatial patterns of turn-taking are studied as simulation results. If there is no excuse, those patterns are generated under a noise-free environment to clarify the intrinsic dynamics of the agents.

## 4 Simulation Results

Simulation was performed with a GA using 15 individuals ($P = 15, E = 4$). After several thousand GA generations, turn-taking is established between the two agents. The basic dynamics of the turn-taking was observed as follows. Two agents adjust their speeds and make turns automatically to switch from the role of evader to chaser and *vice versa*. In the following subsections, we investigate the turn-taking pattern realized from the dynamic repertoire, predictability, adaptability and evolvability concepts.

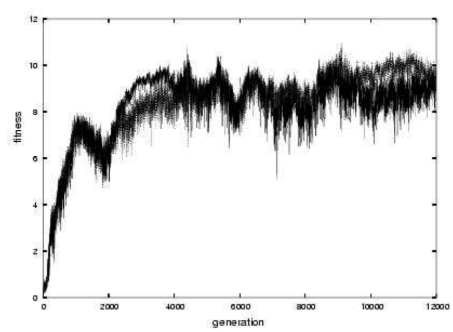


Figure 3: Fitness values of the best agents in two populations at each GA generation for a single run.

### 4.1 Diversity of Dynamic repertoire

First, the evolutionary algorithm effectively functions to improve the turn-taking performance. The development of the performance as a function of GA generations is depicted in Fig. 3. The resulting turn-taking patterns are sensitive to some of the settings. In particular, they are sensitive to the division of the agent population into two. In previous work, we encoded the pair of agents' structures on the same gene [7]. Then we encoded them separately but used a single population. That algorithm can also develop turn-taking behaviour but with much less diversity than the present algorithm. When the agents are on the same gene, it is difficult to show diversity as their net structures are too correlated. With a single population, development of an agent that can take turns with itself (its relatives) is enhanced. Therefore, there is a strong probability that the dynamics of the turn-taking may be tuned for self-turn-taking. To avoid this situation, we used the two-population structure.

Figure 4 shows examples of the spatial trails of an agent from different GA generations with different initial population structures. For the sake of clarity, a single agent's trail is depicted. A paired agent tends to show the same trail with different phases.

We can classify these trail patterns approximately into regular, chaotic and others based on their appearance in space and time. When spatial trails consist of regular curves, and turns are exchanged almost periodically (which corresponds to a turning point on the figures), we call them *regular* turn-taking. On the other hand, if spatial trails have irregular curves with non-periodic turn-taking, we call them *chaotic* turn-taking. The remaining unclassified patterns are discussed below.

In the earlier GA generations, agents with regular turn-taking evolve to yield higher performance (Fig. 4(a) and (b)). The behaviour structure is as follows. One agent follows the other and passes it; then it slows as does the other agent; then both agents simultaneously turn around quickly. This returns the agents to the first phase. A series of behaviour patterns repeats almost periodically and the envelope curve of these trails constitutes a circle by fixing the centre location. In the later GA generations, more chaotic patterns emerge (Fig. 4 (c) to (h)). In contrast to the regular patterns, the turns are exchanged in different places with irregular time intervals. Therefore, the spatio-temporal pattern becomes chaotic and agents move around the entire space.

The evolution of turn-taking type from regular to chaotic is explained as follows. The evolutionary pressure of GA at first allows the agents to move stably in the noisy environment. A structured turn-taking behaviour can only be built up on stable motion dynamics that are insensitive to random noise. As argued briefly in the introduction, noise and intentional action is difficult to distinguish when the agents' motions become chaotic. However, when their actions appear regular, we can interpret that the agents can more easily distinguish noise from the other agent's intentional motion as they show different performance with and without partners' adaptive motions (see §4.3). Therefore, the regular type emerges earlier than the chaotic motion. As shown in Fig. 5, regular turn-taking occurs at almost the same spatial location with different noise series. However, the chaotic type is sensitive to the noise series. The total performance of turn-taking remains high in both cases.

That is, regular turn-taking pattern suppresses a variety of dynamic repertoires. By doing so, it becomes robust against sensory noise. On the other hand, chaotic turn-taking pattern has the potential to develop dynamic repertoire, and therefore it becomes more adaptive, which is studied in §4.4.

Intuitively, agents who can take turns in the presence of noise can take turns perfectly without noise. However, this does not hold for some agents found in later GA generations. As shown in Fig. 6, agents can only take turns when there is sensory noise. We call this phenomenon *Noise-induced* turn-taking. As shown in the figure, there is a strong attractor to a circular motion without exchanging turns. The two agents have different neural structures, and the resulting turn-taking behaviour is generally asymmetrical. Without noise, one agent is never able to take its turn. In addition, it forms an attractor in the sense that adding a small noise cannot break this one-sided behaviour. True turn-taking only emerges above a certain noise level (Fig. 7). In another case, there exist three attractors when there is no sensory noise. One is that agent A chases the rear of agent B closely. Another is the opposite, and the last is that in which both agents chase each other. Each of the three attractors consist of circular orbits. The transition between attractors is caused by noise. Without noise, agents are trapped by one of the attractors.

Compared with these noise-induced behaviours, chaotic turn-takers can spontaneously establish turn-taking behaviour without noise. Even if noise is introduced into the system, chaotic turn-takers can establish turn-taking behaviours independent of the low noise level. That is, they do not utilize noise but suppress the effect of noise to perform turn-taking. Conversely, noise-induced turn-takers need noise to perform turn-taking.

## 4.2 Prediction Capability and Role Switching

These observations were analysed in terms of prediction capability of agents. The agents, after thousands of GA generations, are able to predict their partner's future movements while turn-taking. Three outputs of the recurrent network simulate the other agent's future location and heading from the current input. Fig. 8, shows the precision of predictions and the associated turn-taking patterns. In earlier GA generations,

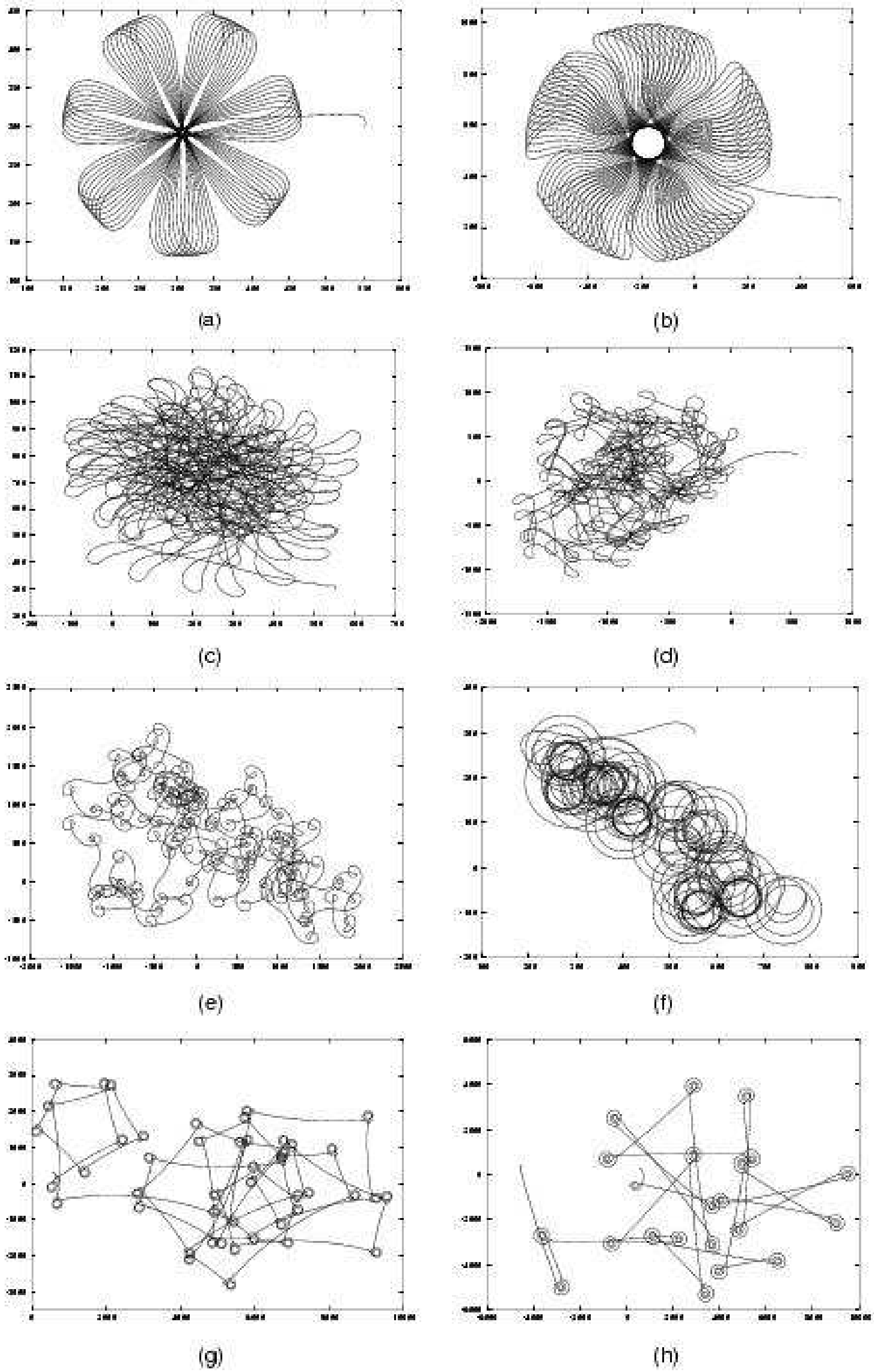


Figure 4: Spatial trails of turn-taking behaviour observed in the simulations. To clarify the qualitative difference of turn-taking structures, a spatial trail of only one of the two agents is shown. The other agent moves around these trails generating similar trails. All games in these graphs are started from (550, 300). (a) and (b) are examples of regular turn-taking behaviour, while the others are examples of chaotic turn-taking behaviour.

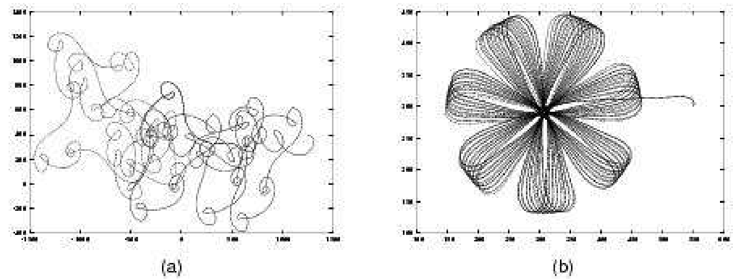


Figure 5: Differences of spatial trails between adaptive agents without noise (solid) and with noise (dotted) are plotted. They start from the same initial points, (550, 300). (a) chaotic turn-taker (b) regular turn-taker

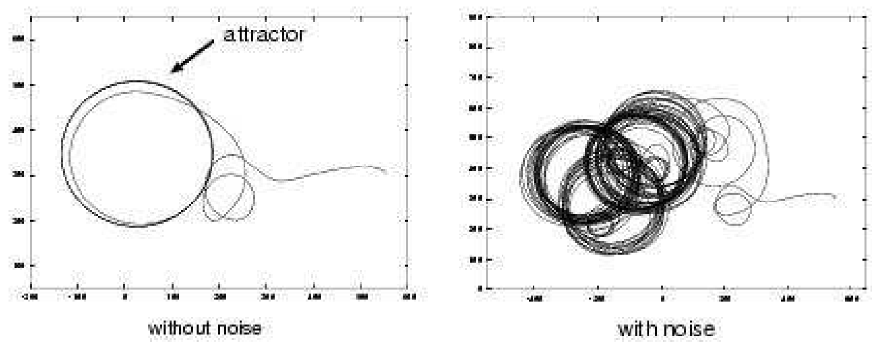


Figure 6: Noise-induced turn-taking behaviour. There is an attractor of role-fixed behaviour. By adding noise to the agents, an agent can slip out of the attractor and successfully perform turn-taking.

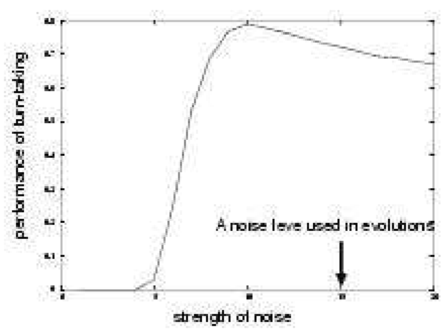


Figure 7: The performance of turn-taking behaviour as a function of noise strength. Below a certain noise level, agents cannot perform turn-taking. Above a certain noise level, agents take advantage of noise to perform turn-taking. This critical noise level is lower than that used in evolution.

one agent's prediction is far better than the other's. In later generations, both predictions are improved. However, through entire GA generations, the predictions almost periodically break down when their turns (roles) are exchanged. As indicated in the figure, the prediction is also perturbed by noisy inputs. However, the effect is much smaller than that of the other agent's action.

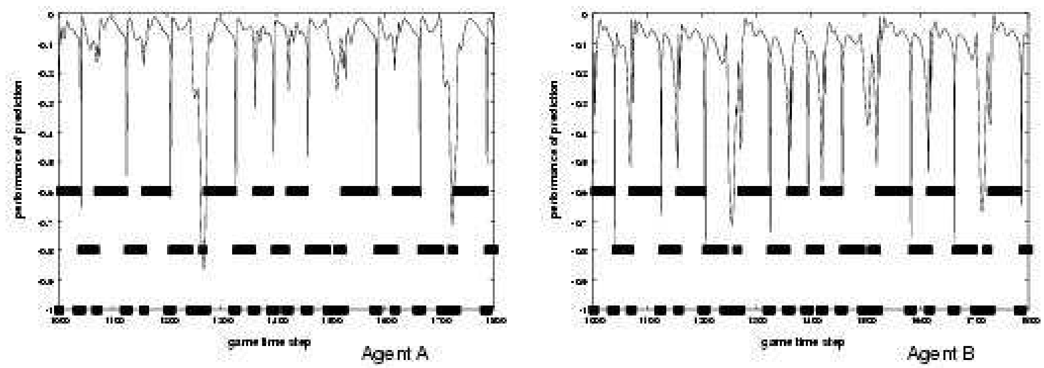


Figure 8: Prediction (top spiky lines) and turns (line segments) are drawn for each agent from 10,000 GA generations. A horizontal line expresses time steps for two agents moving in the two-dimensional arena. The top two line segments correspond to turns of the coupled agents. The bottom segments correspond to times when neither agent has a turn. This shows that the prediction precision decreases sharply when a turn is switched.

It should be noted that these prediction outputs are not designed explicitly to do anything in generating action sequences. However, because they depend on the common context neurons that also control the motion patterns, simulating each other's behaviour and generating the motor outputs have indirect correlations. The correlation between prediction breakdown and the turn-taking performance will be reported elsewhere.

### 4.3 Ongoingness of Interactions

The inherent adaptability of each turn-taking pattern can be studied using its stability in the presence of noise. In other words, we study an agent's ability to discriminate between noise and the adaptive behaviour of the other agent. In this section, we compare the behaviour of "live interaction" with "recorded interaction". The "live interaction" is normal interaction between evolved agents, and the "recorded interaction" is that between an agent and a virtual agent, defined below.

First, we selected the two best agents, A and B, from each population. Turn-taking between these agents was studied without introduced noise. This is what we term "live interaction". The trails of the agents were recorded during the run. Then, turn-taking between agent A and the recorded trail of agent B (i.e., a virtual agent) was conducted. This is what we term "recorded interaction". We perturb the recorded trail and simulate the changes in the turn-taking dynamics.

Figure 9 (a) shows the growth of a discrepancy between A-virtual B and A-perturbed virtual B (chaotic turn-takers). During the initial few hundred steps, no discrepancy was observed. The behaviours are similar as shown in the figure. However, a small noise was amplified and the orbit drastically changed from the original orbit at approximately 800 time steps. In terms of the turn-taking behaviours, the adaptive agent can no longer recover harmonization with the perturbed virtual agent. The agent approaches the trail and tries dynamically to resume the original turn-taking behaviour.

Another example (the agents at 3,000 generations) is shown in Fig. 9 (b). These agents established regular turn-taking. In this case, the agents could cope with the perturbed virtual agent. Note that agents that have constructed regular turn-taking behaviour do not always, but frequently do, have a tendency to cope with a perturbed virtual agent, although this varies with the timing and strength of the perturbation. Sometimes turn-taking behaviour breaks down when more noise is added to the recorded trail. However, there are some examples in which turn-taking recovers after a period of discrepancy.

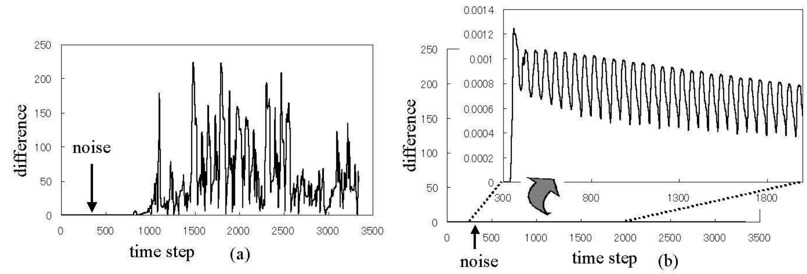


Figure 9: Differences of orbits between agents' trails in a game with an adaptive agent and a recorded trail. A small noise is introduced at 340 time steps. If there is no noise, no difference is observed. Agents used in (a) and (b) correspond to those in Fig. 4 (e) and (a), respectively. The difference is amplified if agents fail to establish turn-taking.

## 4.4 Evolution of Adaptability

Another novel feature of adaptability was examined. We show here that adaptability can generate novel dynamics by constructing new couplings. We examine the behaviours of new couplings between two agents from different GA generations as follows. After the turn-taking performance had attained a satisfactory plateau, we selected two individuals from different generations to play. This was to examine how they performed turn-taking without having the common experience of co-evolution. Taking agents from generations 10,000 and 3,000 as examples, we evaluated the performances of the new pairs for each generation (Fig. 10). In fact, the novel pairs often failed to sustain the same performance as the original pairs. However, the synthesized dynamics often showed novel structures. The examples can be found in Fig.11. Agents that perform chaotic turn-taking after 10,000, 8,000, and 7,000 generations (Fig. 11 (a),(c) and (e)) are coupled with agents from each different generation. As is seen in the figure, the newly coupled agents also show chaotic turn-taking but with a different kind of motion (d). Coupling of generations 1,000–7,000 and 8,000–7,000 shows a similar pattern to that by the agents from generation 7,000, which is shown in (b) and (f).

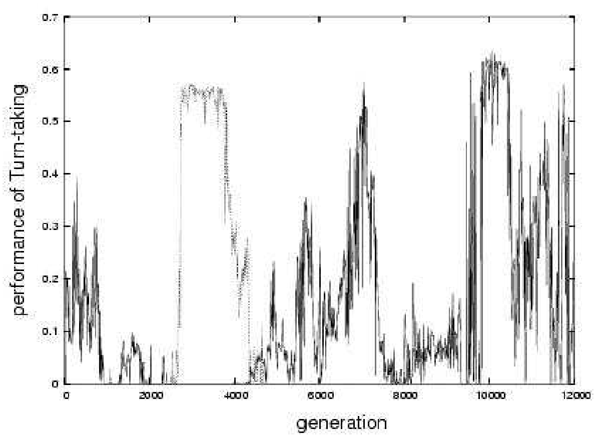


Figure 10: The best agents from the 10,000 (solid line) and the 3,000 (dashed line) GA generations are examined with regard to coupling them with the best agents from different GA generations. The performance of turn-taking of the newly coupled pair is evaluated for each generation. Generally the performance is lower than the original performance of the best pair from each generation, which is approximately 0.6.

In summary, (i) Novel structures sometimes inherit the original pattern of one of the agents but not always, (ii) Agents that readily exhibit chaotic turn-taking pattern lose the original pattern and adapt to the other agent's pattern, and (iii) conversely, regular turn-takers simply retain their original pattern and show little adaptability to a new partner.

The last point is clearly shown in Fig. 12. The regular turn-takers can only achieve higher performance

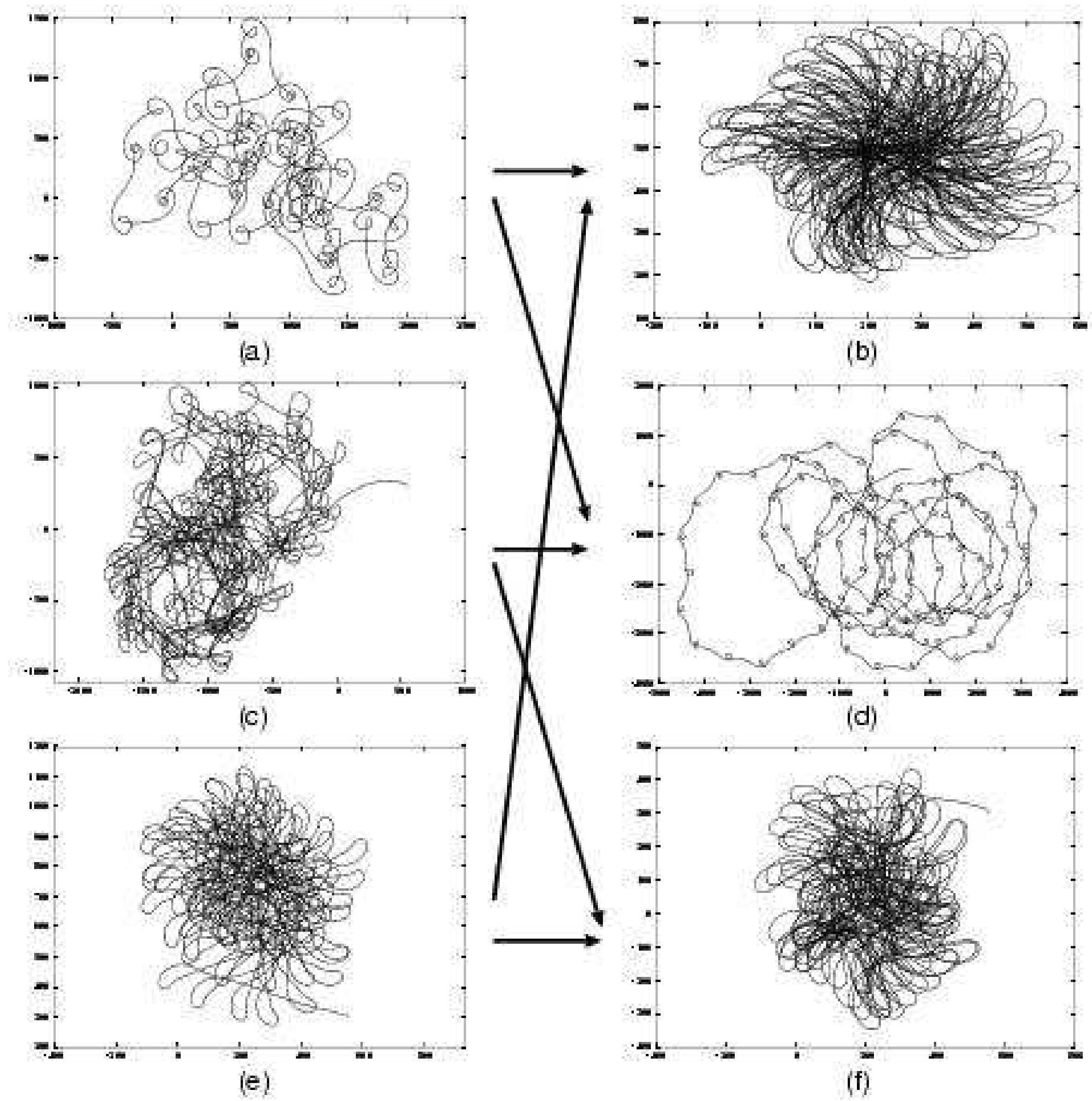


Figure 11: Spatial trails of the original pairs and newly coupled agents at 7,000, 8,000 and 10,000 GA generations. (a), (c) and (e) show the trails of the original pairs at 10,000, 8,000 and 7,000 generations, respectively. On the right, newly coupled agents' trails are shown. (b), (d) and (f) are generated by the best agents at 10,000 vs 7,000, 10,000 vs 8,000, and 8,000 vs 7,000 generations, respectively. (b) and (f) are similar to the trails generated by the original paired agents from the 7,000 generation. On the other hand, (d) shows a new trail.

with agents from near generations (Fig. 10) Our hypothesis is that chaotic turn-takers are more adaptive than regular ones. The observation here confirms the hypothesis, but we should note that performance sometimes differs significantly between populations A and B from the same GA generation. Figure 13 illustrates how turn-taking performance varies from generation to generation. We deduce from this figure that they are basically symmetrical for populations A and B. Sometimes there are notable exceptions—e.g., population A from generation 8,000–10,000 compared with population B from generation 10,000–12,000. It should also be noted that genetically closer agents can collaborate better than more distantly related agents. However, qualitatively, beyond generation 6,000, agents become more adaptive than those of earlier generations.

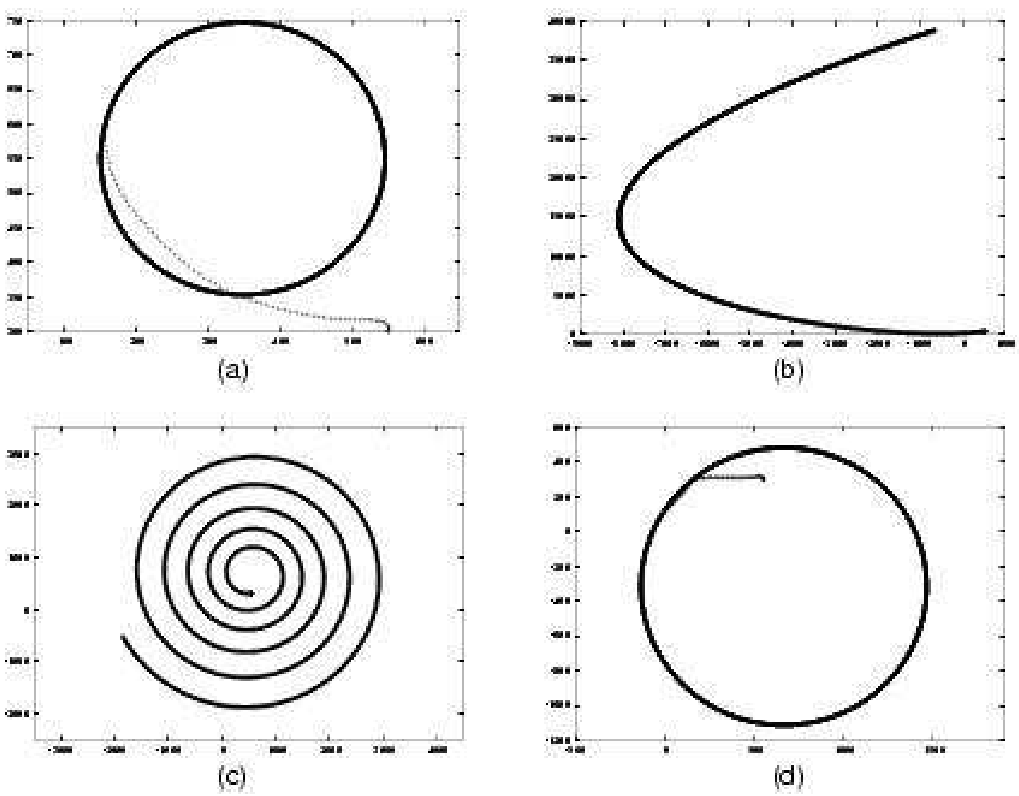


Figure 12: Spatial trails of new couplings of regular and chaotic turn-takers. (a) 3,000 vs 7,000 (b) 3,000 vs 8,000 (c) 3,000 vs 10,000 (d) 3,000 vs 27,280. One agent always chases the partner, and role changing did not occur. Convergence of agents' sensors and motors causes the decrease in behavioural diversity and the interruption of role changing for turn-taking.

The turn-taking pattern resulted from the collaboration of two agents. Therefore, a neural structure in the body of a single agent alone cannot explain the turn-taking dynamics. This is an interesting part of the present study, but at the same time, a gap between the two agents may develop. That is, when one population becomes very adaptive against many others, it is not necessary for the other population to become very adaptive; it may simply become a test data set for the former population to become "universal" turn-takers. As far as we know, such universal turn-takers are yet to evolve. Here we notice that chaotic turn-taker is better at eliciting coordinated behaior from the partner.

It is also worth noting that the "experience" of two agents interacting with each other is a prerequisite for better turn-taking. The history, or the experience, of how agents have collaborated to perform turn-taking determines with whom an agent can take turns. In new pairs, responses of one agent to the other often occur at the wrong time, whereas the original pairs show complete synchronization of turn-taking. That is, we insist that it is not the neural structure but the collaboration of timing and patterning that is responsible for the better turn-taking behaviour. This is true not only for this special type of interaction—i.e., turn-taking—but may be true for cognitive interaction in general. We will argue this point in the final section of this paper.

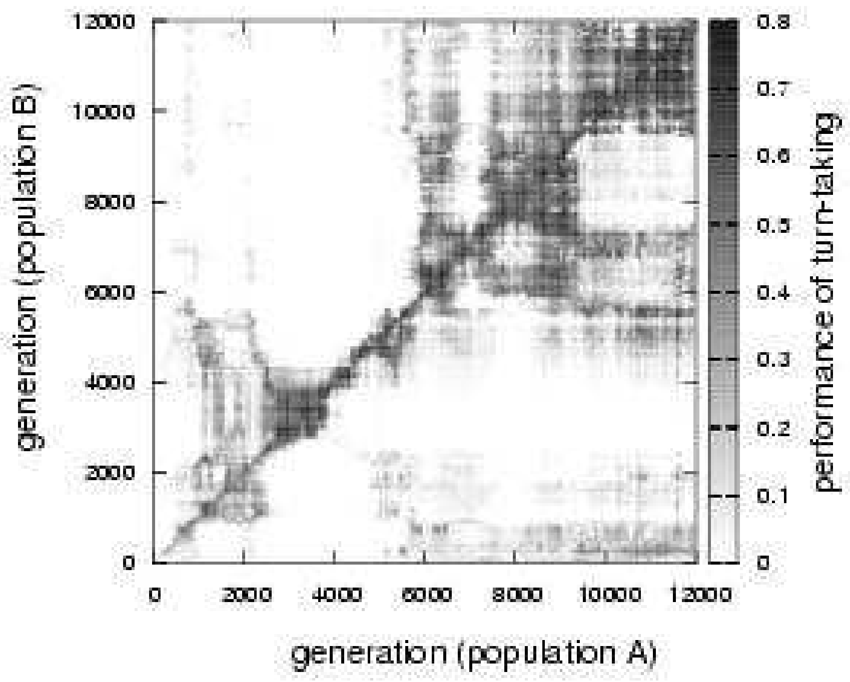


Figure 13: The performance of turn-taking by new couplings with the best agents from all generations of two populations. Beyond 6,000 generations, patterns change from regular to chaotic. The agents after 6,000 generations show a tendency to be able to perform turn-taking with agents from different generations.

## 5 Discussion

It was found in the virtual agents experiment (§4.3), that chaotic turn-takers are much more sensitive to the difference between live and recorded inputs. Their turn-taking patterns are driven by the ongoing interaction. On the other hand, regular turn-takers are relatively insensitive to the difference. As evolution continues, chaotic turn-taking replaces regular turn-taking in the GA simulations. This may be due to regular turn-takers' being less adaptive than chaotic turn-takers in the sense that they can only cope with fewer agents. This is clearly seen in the new coupling experiment §4.4. The coupling with regular turn-takers only generates circular patterns but chaotic turn-takers show various patterns. In summary, we claim that chaotic turn-taking is less robust in the presence of noise but has more adaptability, compared with regular turn-taking.

This complementary relationship between adaptability and robustness has some implications in some empirical experiments. Let us introduce Trevarthen's double-monitor experiments between a baby-infant and its mother [21, 22], and Nadel's mutual imitation experiments [13]. In Trevarthen's experiment, mother and baby-infant only communicate through videos that display their faces to each other. For the baby-infant to engage with the mother, correct style and timing are required. If the recorded video of the mother is displayed to the baby-infant, the baby-infant becomes withdrawn and depressed. Nadel studied how the mutual imitation game progresses between children and discussed a non-affordant means of using objects to trigger the interaction. Children regularly switch between the roles of imitating and being imitated, by having new imitation patterns.

Trevarthen's experiments show that it is not necessarily important for the baby-infant that the mother be displayed on the monitor. It can be assumed that the most important clue during interactions is the ongoing anticipation of a partner. The baby-infant performs some actions and anticipates the mother's reactions reflecting the baby-infant's actions, and this is also true with respect to the mother's anticipation of the baby-infant. Interactions in social behaviour, including turn-taking, can be established when these anticipations are mutually formed dynamically. Furthermore, it is shown by Nadel's experiment that an affordant way of using objects can maintain interaction—i.e. some form of novelty/unpredictability is required. In our simulations, when an agent calculates outputs, this calculation simultaneously affects the internal dynamics. That is, the actions performed form its internal dynamics as much as actions form anticipations in the statement above. The agent receives a partner's actions as inputs that reflect the agent's own actions. We maintain that turn-taking is established when these structures are mutually organized. Turn-taking is therefore broken in the simulation with virtual agents. However, our simulations also show that unpredictability is found when turn-taking occurs. We therefore claim that mutually adaptive coupling of actions and internal dynamics between agents is essential for the establishment of cognitive interaction, which may be related to intersubjectivity.

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