# Simulating Turn-Taking Behaviours with Coupled Dynamical Recognizers

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### Abstract

A coupled dynamical recognizer is proposed as a model for simulating turn-taking behaviour. An agent is modelled as a mobile robot with two wheels. A recurrent neural network is used to produce the motor outputs. By controlling this, agents compete to take turns on a two dimensional arena.

There are two novel aspects to the present study. First, a dynamical recognizer is not only used for producing motor outputs but also to predict the other agent's behaviour. Second, unlike a mere chasing game, turn-taking behaviour is established only when each agent automatically switches from chaser to evader and *vice versa*.

By using the genetic algorithm technique, we show that turn-taking behaviour is developed between two agents. It is worth noting that turn-taking is established only when an agent fails to predict the other agent's behaviour. In other words, the simultaneous generation of stable (predictable) and unstable (unpredictable) dynamics is inevitable to lead to successive turn-taking behaviour. A relationship between joint attention and prediction will be discussed from this and other related works.

## Introduction

Imitation, prediction and theory of mind: these are thought of as mental functions/modules that are useful in explaining and synthesizing cognitive behaviours (J.L.Elman et al., 1996). Artificial cognitive behaviour is also synthesized with those modules (B.Scassellati, 1999). However, it is also true that there are many cognitive behaviours that cannot be understood in terms of such modules.

One possible approach has been taken by Kerstin Dautenhahn with embodied intelligent agent experiments, in which functions of embodiment and of interactions between humans and robots are investigated (K.Dautenhahn, 1999). In the present paper, we instead conduct computer experiments between two cognitive agents and simulate how one agent can, paradoxically, predict the other agent's behaviour but at the same time cannot predict it. This paradox leads to cooperative behaviours, such as successive turn-takings. In terms of dynamical systems, we stipulate that both stable and unstable (manifold) directions must be generated simultaneously to lead to cooperative behaviour patterns. The dynamical systems way of examining cognitive behaviours provides a different view from a mere module-type modelling approach. The main issue of dynamical systems modelling is not to propose an adequate combination of modules, but to study the dynamical rearrangements of modules. In other words, we have to destabilize the functionality of the module itself.

When taking turns for conversation between two persons, without setting any explicit cue to switch speakers people usually avoid overlapping or interrupting each other's speech. Some cues for this include eye contact and the detection of intonation changes. Here we generalize from this 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.

This paper is organized as follows. First, we describe the background motivation of the present study in terms of joint attention in Sect. 2. Then, the concept of dynamical recognizers as cognitive agents is introduced in Sect. 3. In Sect. 4, we explain a model in which the roles of agents are not pre-defined but are determined purely dynamically. In Sect. 5, an evolutionary design for neural nets is shown. The results of simulations are presented in Sect. 6 and Sect. 7 re-examines the results in terms of the internal dynamics of agents. Finally, our discussion and conclusions are presented in Sect. 8.

## Interactivism

Even at a few months of age a baby can predict events and behaviour. Infants almost innately predict events as if they know simple physical laws (R.Baillargeon et al., 1985). It has been argued that guessing what other people think from their behaviour and environment is also developed at an age of 3 to 4 years (S.Baron-Cohen et al., 1985). The latter ability in particular is attributed to a psychological module called a theory of mind. It is also argued that autistic children may lack this theory of mind module and thus are deficient in their ability to predict other persons' behaviour.

On the other hand, joint attention, for example, has also been viewed as an important ability for cognitive development (e.g. see (R.P.Hobson, 1993)). Joint attention is simply defined as a coordinated behaviour among more than two persons. A simple example is a child gesturing at its mother with the aim of getting something. This is not just important in its social context for three or more people, but it is also important for the initiation of interactions between two people. Unlike the ability given by the theory of mind, joint attention is important in introducing "novelty". To continue conversation or to continue play behaviour requires a kind of "novelty" which is defined as "partial" unpredictability. It is well known in developmental studies that infants watch new/surprising events longer. In other words, novelty inherently attracts infants to it and therefore an interaction is established between them and the event. We thus use novelty as a necessary factor to start and maintain interactions.

Novelty thus should be continuously generated to sustain interactions, but at the same time it is also true that novelty cannot be prepared beforehand: it is an ongoing property of the interaction. Joint attention can continuously introduce novelty into the interacting field. Certain types of interactions between "cognitive agents" can synthesize joint attention and thus create novelty.

Joint attention and prediction are two sides of the one coin. We have argued that they can only be treated as dynamical characteristics. This idea has been examined in several simulation examples, e.g., a language game (I.Igari and T.Ikegami, 2001), the iterated prisoner's dilemma game (T.Ikegami and M.Taiji, 1998) and some other game systems (T.Ikegami and M.Taiji, 1999). In the following, we introduce a basic framework called coupled dynamical recognizers and showing how we can understand turn-taking behaviours with stable and unstable dynamics.

## Coupled dynamical recognizers

We propose a dynamical systems way of studying interaction between two agents, where each agent predicts the other agent's future move and also determines its own action.

As Pollack first explicitly showed (J.B.Pollack, 1991), a recurrent neural network can imitate the behaviour of some finite automaton. Therefore the reucurrent neural network is often called a dynamical recognizer(DR).

By coupling two DRs, we have simulated the iterated prisoner's dilemma game (T.Ikegami and M.Taiji, 1998; M.Taiji and T.Ikegami, 1999), Dubey's game (T.Ikegami and M.Taiji, 1999) and some language games (I.Igari and T.Ikegami, 2001). Those simulations show that i) DR can simulate the infinite state machine-like behaviour and ii)the instability of coupled DR enables mutual cooperation, temporal optimal behaviour and topic developments in discourse.

In the present study, we show how turn-taking behaviour is synthesized by the instability generated by the coupled DRs. Different from our previous works, the present model only deals with analogue input/output values so that it is easier to analyse the temporal behaviour from a dynamical systems point of view. Also, it should be remarked that an important part of turn-taking behaviour is "temporal role changing". This study therefore focuses on different perspectives from the fixed role-playing games (e.g. a pursuit-evasion game) (D.Cliff and G.F.Miller, 1996).

Based on this and the previous related simulations, we discuss how cooperative behaviour such as joint attention is developed not by the nested predictions of agents but by the nature of the interaction itself. One of our main messages is that joint attention can be taken as a behaviour of sustaining uncertainty (i.e. autonomy) instead of removing it. This notion is somehow adequate to describe what we call 'play behaviour'.

## The model

Turn-taking behaviour is observed when two people interact with each other such as during conversation or when playing a game of tag. One does not keep speaking all the time or one is not always a chaser. Temporal role-changing is performed spontaneously based on the history of interactions in such games. Here, we modelled playing tag in a physical space by extending the conventional pursuit-evasion game.

There have been some other studies in developing the controllers of agents' motions in physical spaces, based on the game of tag, where one plays a role of chaser and the other evader. In those models, the agents' roles are predefined and fixed all the time. The agents acquire controllers for their specified roles through learning or evolutionary processes (D.Cliff and G.F.Miller, 1996). These conventional game models have mainly focussed on the histories of acquired strategies, designs of evolutionary mechanisms or the co-evolutionary algorithm itself.

In our game model, the role of chaser or evader is not given to agents in advance. The objective of the agents in the game is to get behind each other. Becuase the agents cannot get behind each other simultaneously, the objective is not achieved if both agents play chaser. Of course, if both agents play evader, mutual turn-taking cannot be achieved 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. But mere symmetry breaking is not sufficient: temporal role-changing is also required. By using the coupled DRs, we focus on how turn-taking dynamics self-organize.

There are also some game models in which the roles are not predefined (C.W.Reynolds, 1995; E.A.DiPaolo, 2000). Reynolds showed that the abilities of chasing and evading are also evolved simultaneously by Genetic Programming in a game of Tag, which is a symmetrical pursuit-evasion game. The variety of the behaviours of agents adapting to their environments is worth noting. In Reynolds' game, a switching between evader and chaser is predefined to happen when both agents come into physical contact. The difference between Reynolds' model and ours is the spontaneous emergence of behaviour. Whether an agent plays a role of a chaser or an evader will be dynamically determined in our model. On the other hand, social coordination is studied with agents that interact acoustically in Di Paolo's model. In this, the objective of agents is not chasing or evading but approaching each other using only acoustic interactions. In this model, each agent can tell the others position from the signal the other is emitting, but their receiving and emitting signals interfere with each other. To avoid interference, their emission timings are entrained in an anti-phase state and the resulting behaviour resembles turn-taking process. There is a difference between Di Paolo's turn-taking and ours. It is similar in that turn-taking behaviour is established by the coordination of agents through a history of their interactions. However, Di Paolo's turn-taking is a result of anti-phase signals for avoiding signal interference. The advantage of our model for identifying the turn-taking event is that we can analyse it by predicting capability. By doing this, we can make connections between the present simulation and general cognitive behaviour: for example joint attention.

## Game and Environment

Each agent here has a circular body of radius R, with two diametrically opposed motors (Fig. 1). The motors can take the agent backwards and forward in a 2-D unstructured and unlimited arena. Each agent's move is based on the following equation of motion:

$$M\ddot{x} + D_1\dot{x} + f_1 + f_2 = 0, \quad (1)$$
$$I\ddot{\theta} + D_2\dot{\theta} + \tau(f_1, f_2) = 0, \quad (2)$$

where $f_1$ and $f_2$ are the forward driving force given by two motors, $\theta$ denotes a rotational angle, and $\tau$ gives the torque. $D_1$ and $D_2$ denote the resistance coefficients of driving force and torque, respectively. $M$ is the mass and $I$ is the moment of inertia. In the simulation, we iterate the equations using the Runge-Kutta method.

We assume no collision between agents because we mainly focus on the internal dynamics of agents that generates turn-taking. What is important for agents is predicting the behaviour of a partner and acting cooperatively in taking turns.

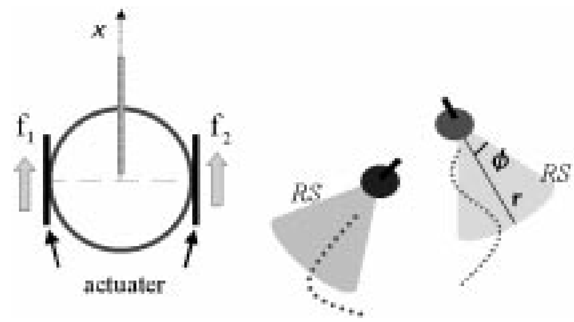



Figure 1: Left: a schematic view of the mobile robot with two wheels (actuators). It computes the forward force vector and the torque strength from the force vector $(f_1, f_2)$ on each actuator. Right: Two mobile robots interact to perform turn-taking behaviour by sensing each other's position and direction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

## Agents

An agent receives the other agent's position and the head orientation relative to the viewpoint forming their sensor inputs. They move freely in the arena by using two motors' outputs, which are computed at each game time-step. The agents compute the prediction of the other one's next relative position and relative orientation via five outputs from three inputs. We designed the agents with recurrent neural networks (Fig. 2)and evolved them by the genetic algorithm(GA). Recurrent neural networks have been applied for evolving relevant controllers of agents that determine their behaviour and motion pattern.

One remarkable characteristic of using recurrent neural networks is that we can make internal models of the other one, so that the other agent's image is represented by complicated geometrical patterns in a context space. This characteristic is useful to clarify the relationship between the internal dynamics and turn-taking behaviour. The dynamics of the recurrent neural network are expressed by the following equations at the game time-step $t$,

$$h_j(t) = g\Big(\sum_i w_{ij} y_i(t) + \sum_l w'_{lj} c_l(t-1)\Big), \quad (3)$$
$$z_k(t) = g\Big(\sum_j u_{jk} h_j(t)\Big), \quad (4)$$
$$c_l(t) = g\Big(\sum_l u'_{jl} h_j(t)\Big), \quad (5)$$
$$g(x) = 1/(1 + \exp^{-x}), \quad (6)$$

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

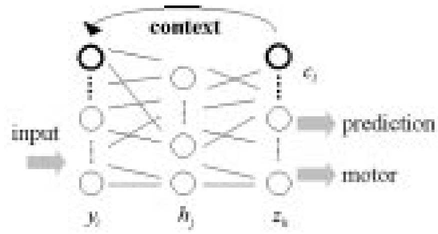



Figure 2: A recurrent neural network with three layers as a dynamical recognizer. Input nodes receive the other agent's relative position. The last layer consists of three kinds of nodes: context, prediction and motor. Context nodes feed back to the input layer. Prediction nodes predict the other's relative position in the future. Motor nodes provides the torque of an agent.

$u'_{jl}$ denote the weights from input to hidden, hidden to output, context to hidden and hidden to context, respectively.

## Evolutionary design of neural architecture

Each agent with a recurrent neural network needs to change adaptively and to update the weights according to the behaviour of another agent. Therefore, GA is applied to evolve the structures of the neural networks. The weight set of the neural networks as phenotype is directly encoded by the genotype that is a vector representation of the real weight values in our GA design.

We also designed each chromosome, which is composed of two parts, each encoding for the weights of one of the two agents (Fig. 3), because turn-taking patterns require a certain degree of behavioural coordination (E.A.DiPaolo, 2000). The fitness of the chromosome is based on the performance of the two agents. In the case that a single genome is assigned to one agent, each agent's objective is individually optimized. This means that the fitness function becomes competitive. This situation can be interpreted as a non-cooperative game by game theory. It is difficult to acquire turn-taking behaviour by having independent agent coding under a competitive fitness function. Therefore, we introduced the coding of a single genome holding two weight sets. Although, this GA coding is relevant for our purpose to see what sort of dynamics can synthesize turn-taking, we cannot state how such dynamics are attained from scratch.

In our GA schema, a rank-based selection is used as a search technique with a fixed population, in which the phenotype of each individual represents a pair of agents. Our evolutionary process develops as follows. At first, the number $P$ of individuals in the population is initialized with randomized weight values. Then, we calculate the fitness of each individual based on the results of the movements of agents in a match. Each match consists of (T=600) time steps. The fitness of turn-taking is a function of coordinated behaviour. Fitness takes the highest value 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 the lower fitness values. Two agents play $N$ matches with different initial values, while calculating the fitness by averaging over initial configurations. The fitness of gene $i$ is calculated as follows:

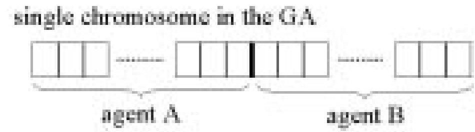



Figure 3: A chromosome used in the GA which is composed of two parts. Each encodes the real value of the weight set of one of the two agents.

$$Fitness_i = s_1 \times Fitness_i^{turn} + s_2 \times Fitness_i^{predict}, \quad (7)$$

$$Fitness_i^{turn} = \frac{1}{N}\sum^{N}\left(\sum_t F_{a_i}(t) \times \sum_t F_{b_i}(t)\right), \quad (8)$$

$$F_a(t) = \left\{ \begin{array}{ll} 1 & Pos_a(t) \in RS_b(t) \\ 0 & Pos_a(t) \notin RS_b(t) \end{array} \right\}, \quad (9)$$

$$Fitness_i^{predict} = -\frac{1}{N}\sum^{N}\left(\sum_t P_{a_i}(t) \times \sum_t P_{b_i}(t)\right), \quad (10)$$

$$P_a(t) = (Pos_b(t) - Pos_{a\to b}(t))^2, \quad (11)$$

where $a_i$ and $b_i$ are agents coded by the gene $i$. $Pos_{a_i}(t)$ represents the position of agent $a_i$, at time $t$ in the match and $RS$ indicates the space behind the other agent, which is specified by two parameters, $r$ and $\phi$ (see Fig. 1). The agent in this scope is said to be in his turn and getting a point. $Pos_{a\to b}$ denotes $a$'s prediction of $b$'s relative position, which is used to calculate the precision of the prediction. According to the fitness function for turns, the fitness value becomes lower if only one agent takes turns in the match. To achieve the higher fitness, both agents need to take turns equally. This fitness function thus makes agents evolve so that the roles of pursuer and evader alternate in a match. After the calculation of fitness, crossover and mutation operations are performed using a rank-based selection. The generations proceed by repeating this process and the weights of the recurrent neural network are evolved.

## Simulation results

Simulation is performed on GA with 20 individuals. Figure 4 shows the fitness against the generations in the GA. As is seen in the figure, the performance of two players at each GA generation fluctuates widely. We attribute this

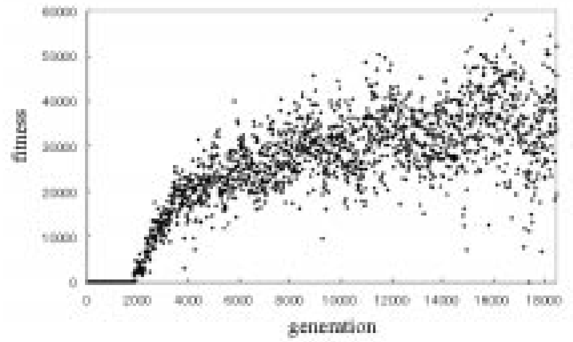



Figure 4: Fitness value of the best agent of each GA generation for a single run. Around 1800 generations, the fitness suddenly takes off and is saturated around 15000 generations. Dynamics of agents at 2500 generations and 18000 generations will be analysed in detail through this paper. The population size, mutation and crossover rates in the GA are set to 20, 0.9, and 0.1, respectively.

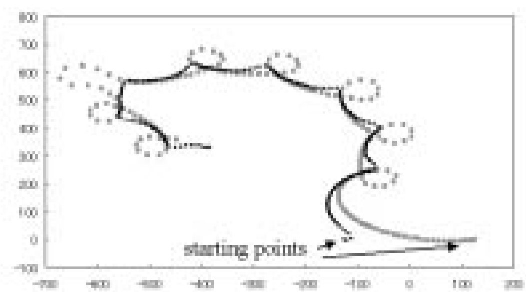



Figure 5: Spatial trails of two agents from generation 2500 in the GA are overlaid on a two dimensional arena. In the text we call one agent A and the other B. The dark coloured trail is agent B's and the light coloured is agent A's. Here agent A takes more turns than B.

to the fact that good performance is found only in some narrow parameter ranges. As both players fine-tune to each other, a red queen-like co-evolution occurs here.

In the earlier GA stages, two agents can initially approach closely from any position. However, soon the symmetry of their dynamics and the associated roles break down. As is seen in Fig. 5, agent A moves around quickly, making small circles while agent B moves slowly with spiky carves. The role of the agent A becomes a chaser and that of the agent B becomes an evader. As a result, agent A is rewarded more than agent B because agent A takes more turns than agent B does. In the later GA stages, their rewards become more equal and coordinated behaviour is developed (see Fig. 6). Agent B cooperatively adjusts its speed and gets more rewards.

In the earlier stages, their temporal behaviours can

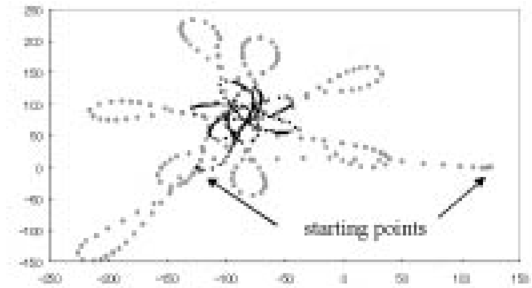



Figure 6: Spatial trails of two agents from generation 18000 in the GA are overlaid on a two dimensional arena. Here both agent A (light colour) and B (dark colour) can take turns equally.

be described as follows: agent A chases agent B and at a certain point agent B abruptly escapes but soon A catches up with B; in the later stage, B gradually slows down to get its turn, while A holds the same local motion. This picture is also clear from Fig. 7 and 8. Fig. 8 shows that both A and B make turns as positive torques are generated synchronously. Therefore, evolution looks successful in the sense that rewards will be equally distributed as the GA time proceeds.

On the other hand, the dynamics which support equal rewards cannot become symmetric. This point will be discussed in the context space analysis.

This observation is now analysed by studying its prediction capability. Three outputs of the recurrent network simulate the other agent's future relative position and orientation. Those outputs are not recruited explicitly for doing anything in generating action sequences. However, because they depend on the common context neurons which determine the motion patterns, simulating each others behaviour and generating the motor outputs has indirect correlations. In Fig. 9, we show that the precision of predictions and the turn-associated sequences. In the earlier stages, B's prediction is almost always worse than A's, but in the later stages both predictions are improved but almost periodically break down when their turns are exchanged. The corresponding turns are displayed with piece-wise lines in the figure. It is worth noting that turn exchanges occur when predictions break down, while prediction holds for each turn holding phase. The spatio-temporal dynamics of the exchange phase look irregular, so that the space trails cannot form a circle. This reminds us of the heteroclinic cycles often observed in replicator dynamics (K.Hashimoto and T.Ikegami, 2001). A system is attracted to a saddle point along the stable manifold most of the time course. However, in the neighbours of the saddle point, the system is repelled from the saddle along the unstable manifold, again being attracted to other saddle points. Therefore almost periodic motions are separated

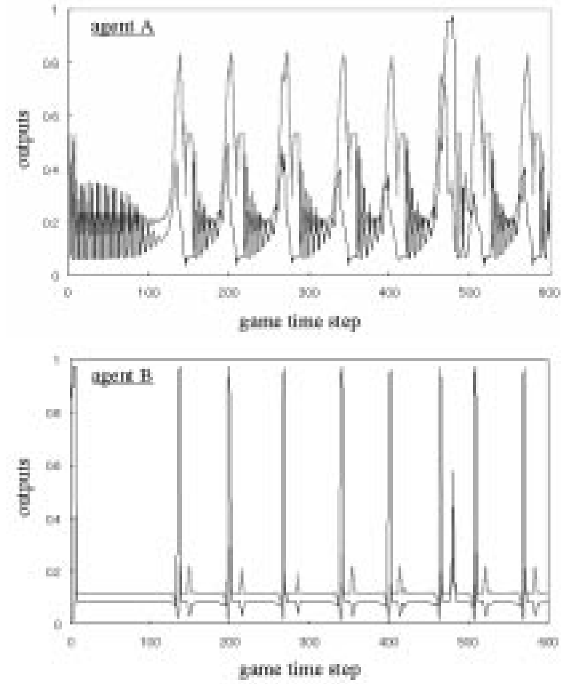



Figure 7: Dynamics of force amplitude on the left (light) and right (dark) actuators at generation 2500 in the GA. Agent A (the top graph) takes turns while agent B (the bottom graph) cannot. The spiky event corresponds to when A and B move apart in opposite directions. In between the successive spikes, A holds its turn.

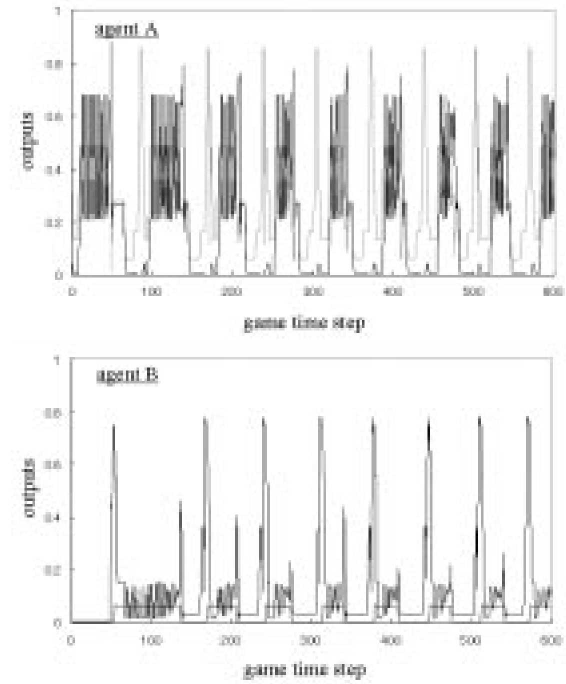



Figure 8: Dynamics of force amplitude on the left (light) and right (dark) actuators at generation 18000 in the GA. Both agent A (the top graph) and B (the bottom graph) can take turns equally. The spiky event now corresponds to switching turns from A to B and vice versa. A's turn corresponds to where both agents' forces oscillate, while in B's turn, the forces become constant. This asymmetry is reflected in the dynamics of prediction and the images in the context space plot.

by chaotic transients. This generation of stable/unstable dynamics is inevitable to produce the equal turn-taking behaviours. To demonstrate this point more clearly, we show context space plots of recurrent nets in the next section.

## Context Space Plots

To see how well a dynamical recognizer (DR) learned the given automaton, we examine geometrical patterns in the "context space", i.e., a plot of context neuron states against possible input states. If a DR can successfully imitate the given finite automaton, then the context space plotting will show finite islands of clusters. A clear correspondence is observed between each cluster and a node of the finite automaton. When the DR fails to imitate, or when the target function cannot be expressed as a finite automaton, the context space plotting shows a stretched and folded, fractal-like structure. Thus the context space plot characterizes the functional behaviour of a given recurrent neural network as a DR.

We present how the context space plots change in the earlier and later stages of the GA experiment (corresponding to Fig. 10 and 11). We notice that less clear patterns emerge in the context space in the earlier stages.

In the context space of agent A, it is shown that there are clusters corresponding to the state of A's turns and those of B's turns. Those clusters are still distributed widely in Fig. 10. On the other hand, clusters are separated in the later stages. In particular, the context space of agent A has two symmetrical internal states corresponding to A's and B's turns. B's context space also separates its internal states but they do not look symmetric, as B's turn is corresponding to a point cluster. This asymmetry between A's and B's context space pattern reflects that A and B have different dynamics. Concerning Fig. 5 and 6, we see that agents A and B move in opposite directions to break A's turn in the earlier stages. On the other hand, both agents move in the same direction to sustain both turns in the later stages. The asymmetry in dynamics comes from the fact that the agent A always makes big circles and B makes small ones. Agent A just outruns B instead of exchanging turns in the earlier stages. However, agent B slows down when A is outrunning B, then A stays in the same direction to support B's turn in the latter stages. Therefore we argue that those are

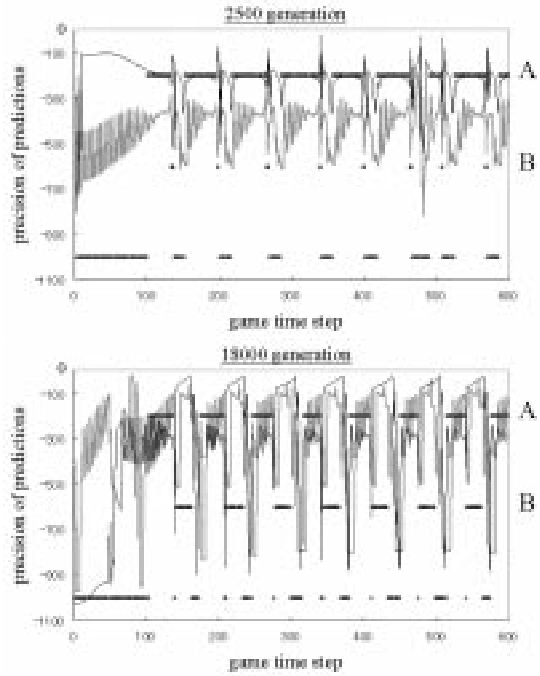



Figure 9: Dynamics of prediction precisions (light and dark) and turns (bold) are presented for generation 2500 in the GA (top) and generation 18000 in the GA (bottom). Prediction curves oscillate in time corresponding to Fig. 7 and 8. Turns are indicated in three discrete levels. The top level corresponds to A's turn, the middle to B's turn and the bottom to no one's turn. As is clearly seen from these graphs, predictions become worse when agents switch their turns from one to the other. In the top graph, B never takes its turn. In the bottom, B's turn is accompanied with predictions of relatively higher precisions, becuase the dynamics looks more regular in B's turn.

cooperative dynamics that sustains mutual turn-taking. The symmetrical separation of A's and B's turns in A's context space suggest that A can perceive both turns equally.

Here we only studied asymmetric solutions in that the two agents have different internal dynamics so that their spatio-temporal dynamics are not the same. However, we also found symmetric solutions with some different net architectures. In this case, two agents tend to move back and forth on the same circle. These results will be reported elsewhere (H.Iizuka and T.Ikegami, ).

## Discussions

It is difficult to have temporal cooperative solution based on the traditional game theories. The present turn-taking behaviour can be taken as a temporal solution of a given game. The game called a battle of sex (J.Maynard-Smith, 1982) cannot generate an apparent optimal solution, i.e. period 2 behaviour. The three-person exclusion game also has period 3 optimal behaviour. In this case, Akiyama and Kaneko show that multiple periods of 3 appear through evolutionary dynamics (E.Akiyama and K.Kaneko, 2000). The prisoner's dilemma game has a unique Nash solution, (defection, defection). But the iterated prisoner's dilemma (IPD) game can have mutual cooperation via a tit-for-tat strategy. In the IPD game, a periodic solution appears when we introduce mistakes. Dubey's space game has a unique Nash equilibrium with piece-wise linear pareto-optimal regions. Ikegami and Taiji show that the pareto-optimal solution can be realized via coupled dynamical recognizers (T.Ikegami and M.Taiji, 1999). In the temporal solution, each agent's models of the other player temporally changes from a finite state machine-like to a strange ones.

In case of the real IPD game among humans, it is often reported that defection repeatedly takes place (T.Yamagishi, 1995). We attribute this deviation from the requirements of the game theory to belief structures of players. A Turing machine cannot be a rational player if he can not decide whether the other player is rational or not, which was proved to be impossible by Anderlini (L.Anderlini, 1990). A belief structure is an internally generated structure, with which we regulate interaction with other people. A simple notion of the belief structure is prediction action. The prediction load of dynamical recognizers in this model can be compared to the belief structure of players. Belief structure in general requires extension of an internal model to simulate what other players are going to play. Because any internal model cannot be complete, we expect to see the differences between the extension and the real. The difference thus perturbs belief structures. By allowing this perturbation, players can take and exchange their turns almost periodically.

In other words, the difficulty in satisfying both taking and losing turns provides an apparent paradox. Taking turns requires first to approach other player from its rear side. Therefore, prediction of the other one's dynamics will help taking turns and good prediction phases generate stable orbits. Losing turns, on the contrary, requires losing predictions. Dynamics becomes irregular so that prediction is difficult to hold; yet it is difficult to say whether losing prediction causes changing turns or vice versa. But at least this paradoxical situation makes the dynamics different from the usual chasing games.

Our main message here is that two complementary characteristics, predictability and uncertainty (i.e. unpredictability) are required to maintain interactions between cognitive agents. This notion sets out a new way of understanding cognitive functions between two people. Almost innately, infants seem to pay attention to the "novelty" of their surroundings. At the same time, infants start to interact with their carers and the inter-

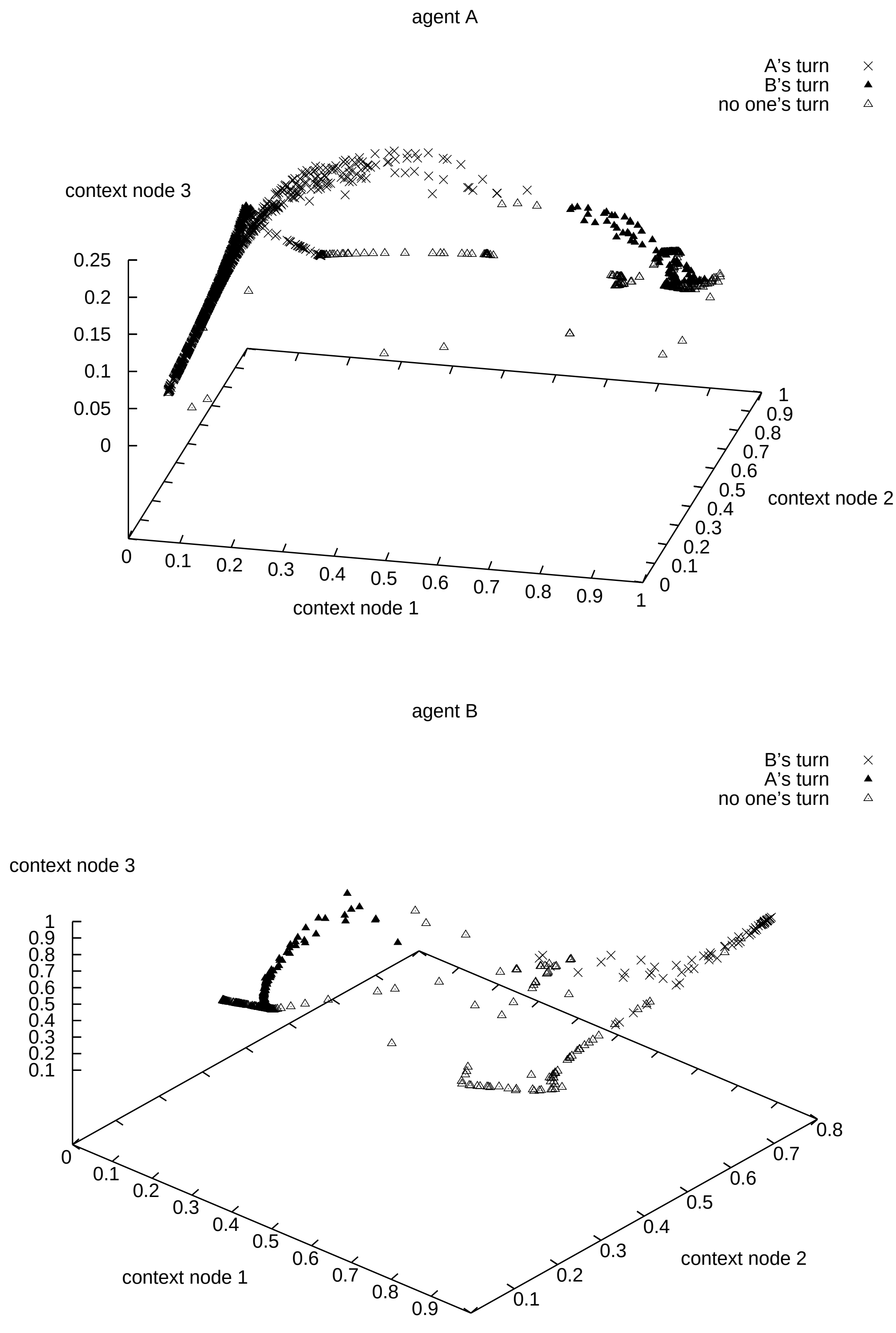
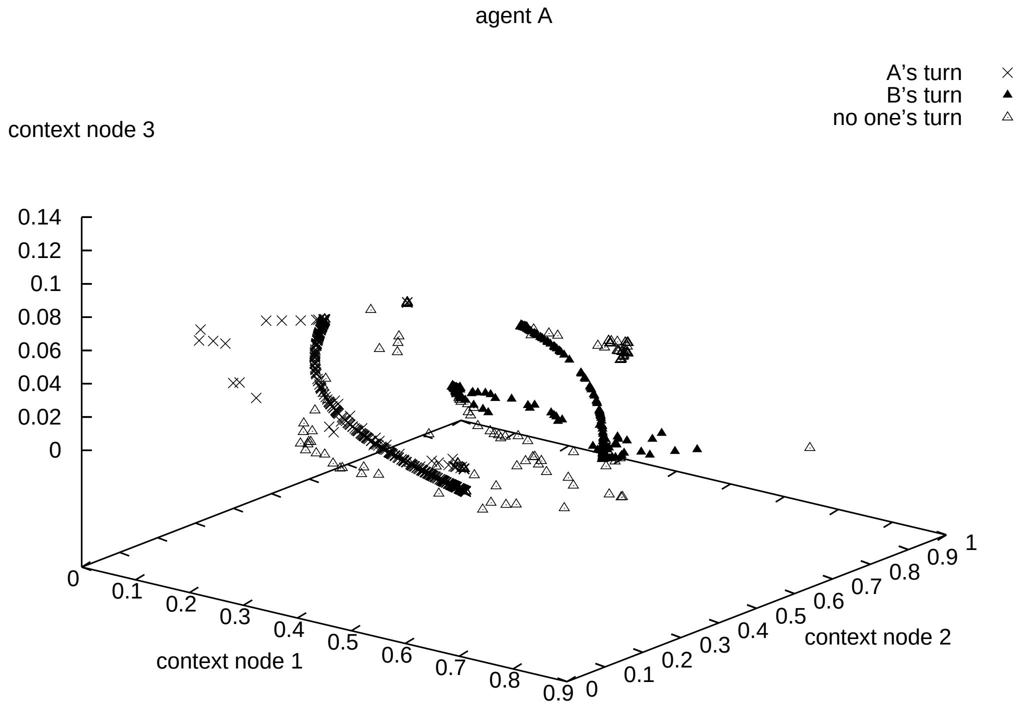



Figure 10: Context space plots for agents A (top) and B (bottom). These are the return maps of three context nodes obtained by plotting successive values of the context nodes for agents at generation 2500 in the GA. Points correspond to A's turn, B's turn or no one's turn.



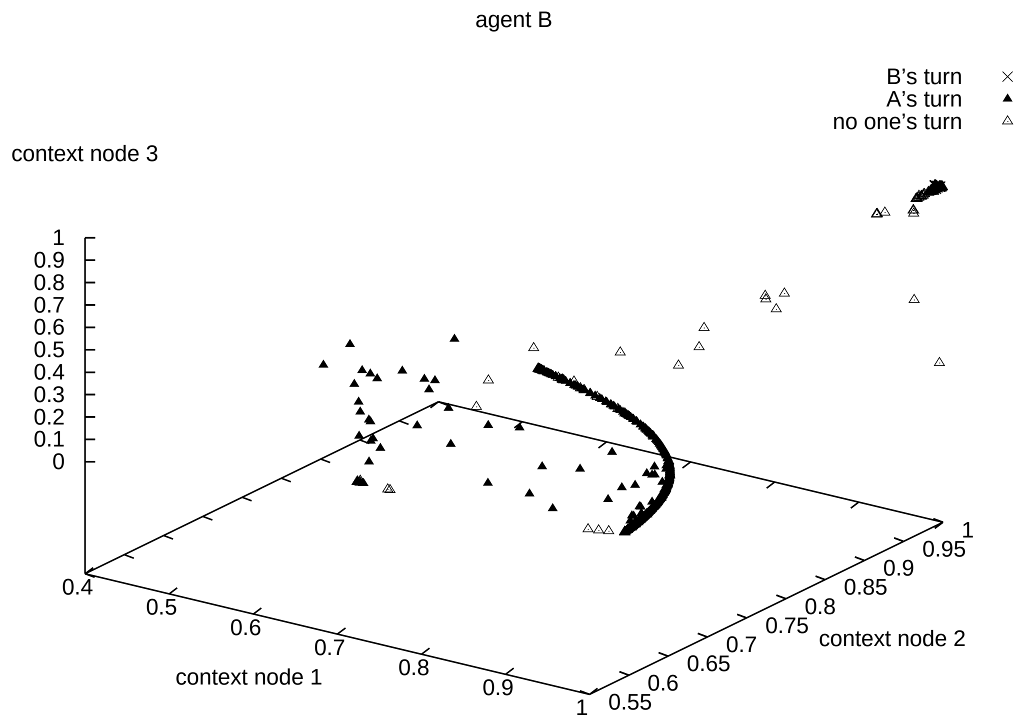




Figure 11: Context space plots for agents A (top) and B (bottom) at generation 18000 in the GA. Points of A's turn and B's turn are more structured than those at generation 2500 in the GA.

action is usually sustained stably. A novelty in the carer, however, is not apparent nor prepared beforehand. It is constantly generated in the way of the interaction between an infant and a carer. What is the underlying mechanism of generating novelty and holding the interaction itself? The present turn-taking simulation partially answers this question. Further, based on our series of studies we can classify cognitive prediction and joint attention into two classes, respectively. Those are hot/cold prediction and tool/goal joint attention (R.Uno and T.Ikegami, 2002). Prediction generally does not need other cognitive agents. Joint attention generally assumes that there are two or more agents. When we say cognitive agents, they have their own intentions and autonomous motions (i.e. autonomy). If prediction presumes autonomy in the other persons, we term the prediction "hot", otherwise "cold". Joint attention concerns how one can associate/synchronize one's intention with others. If a person uses joint attention as a tool to achieve a goal (e.g. establishing joint attention to let your dog pick up a ball), we call it "tool joint attention". But if a person takes joint attention itself as a goal, we call it "goal joint attention". For example, two people looking at the same sunset establish goal joint attention as it does not require further achievements.

Hot prediction and goal joint attention will not suppress the uncertainty found in the other one's autonomy. Instead they positively admire the existence of the autonomy. What is interesting with the goal joint attention is that the goal of the interaction is the interaction itself, to maintain the interaction under the uncertainty caused by the autonomy. In other words, joint attention is a product of interaction among agents. The present simulation suggests that unpredictability is a prerequisite to maintain joint attention (cooperative interaction), because the unpredictability causes turn exchanges. The selected agents do not evolve complete predictability to attain joint attention. As the result, they can continually interact with each other and perform successive turn-takings.

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