Adaptive Coupling and Intersubjectivity in Simulated Turn-taking Behaviour

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Abstract. Turn-taking behaviour is simulated with 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. On the other hand, regular turn-takers are comparatively insensitive to noisy inputs due to their restricted dynamics. From various observations, including turn-taking with virtual agents, we claim that the chaotic turn-taking agents become less robust when coping with virtual agents but at the same time, those agents are more adaptable to each other than the regular turn-taking agents. All these findings are discussed and compared with Trevarthen's double monitor experiments.

1 Introduction

Intersubjectivity is a term used in psychology and philosophy to describe the sharing of mental states and intentions with others. Trevarthen was the first person to notice its importance [11]. This intersubjectivity is strongly connected to social behaviour between two or more entities. Interacting socially with others requires more than mere interaction and synchronization of actions but coordinated behaviour of entities that have rich dynamics. There are many ways to understand psychological phenomena by computer simulations and robot experiments rather than by studying human behaviour directly [2, 10].

By conceiving couplings between agents with rich internal dynamics, we should develop new ways of understanding their dynamics [4–6]. 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 to the fixed role-playing games (e.g. a pursuit-evasion game [1]). Here we take turn-taking as the simplest example that shows diversity of dynamics. It is necessary for turn-taking behaviour to autonomously exchange roles along with the 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 any 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 net that computes the output from inputs. Thus, the coupling between agents means a coupling of anticipatory systems with intrinsic dynamics.

By introducing the agent architecture, evolutionary algorithm and the turn-taking environments, we explore three topics in our simulations. They are dynamics repertoire, noise-driven turn-taking behaviour and turn-taking with virtual agents. The present paper is a continuation of the work of the previous study [8]. The basic model set-up is the same, but here we have a greater variety of turn-taking behaviours, which enables us to perform experiments described in this paper.

2 The model

We modelled a playing 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 [9, 3]. Reynolds showed that the abilities of chasing and evading also evolve simultaneously by genetic programming in a game of tag, which is a symmetrical pursuit-evasion game. The variety of the behaviour of agents adapting to their environments is worth noting. In Reynolds' game, 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 the role of a chaser or an evader will be dynamically determined in our model. On the other hand, Di Paolo modelled and studied social coordination with agents that interact acoustically. 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 a 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 forward in a two-dimensional unstructured and unlimited arena. The motion is described by the following equation of motion of an agent's heading angle (θ) and the velocity

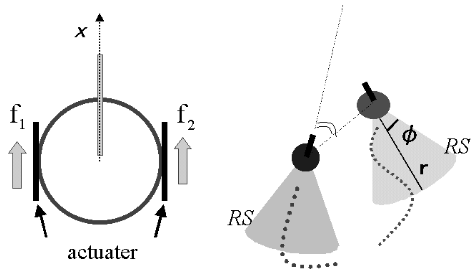

Fig. 1. Left: a schematic view of the mobile robot with two wheels (actuators). It computes the forward force vector and the torque strength from the force vector (f_1, f_2) on each actuator. Right: Two mobile robots interact to perform turn-taking behaviour by sensing each other's position, relative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

(v) in that direction.

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

where f_1 and f_2 are the forward driving force, and τ denotes the torque. Each agent has a heading angle, which is denoted by θ. 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, 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 the 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, 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. However, mere symmetry-breaking is not sufficient; temporal role-changing is also required. By using recurrent neural networks, we focus on how the turn-taking dynamics are self-organized.

2.2 Agents

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. They move freely in the arena using two motors, the outputs of which are computed at every game time-step. The agent predicts the other's next relative position, assigned three output neurons. The dynamics of the recurrent neural

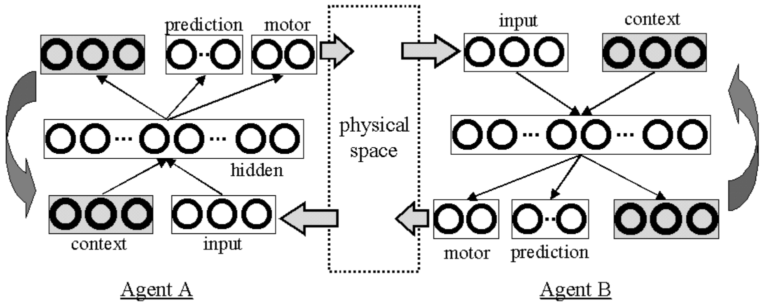

Fig. 2. Recurrent neural networks with three layers. Input nodes receive the other agent's relative position. The last layer consists of three types of nodes: context, prediction and motor output. Context nodes feed back to the input layer. Prediction nodes output the other's relative position in the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

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, while the parameter b gives a bias node. In this paper, we do not treat the results of predictions, which are discussed in [7]. This network architecture evolves using a genetic algorithm, which is explained in the following section.

3 Evolutionary design of neural architecture

We update the weights according to 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 among genetically close agents. As a result, a player has to play against itself, which we want 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 equally exchange turns are evaluated to have 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 the lower fitness values. Practically, the fitness of an agent a from a population (A) against an agent 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 an agent gets behind, the other agent has, by definition, its turn and the rear scope is specified as RS, which is parameterized by two parameters r and ϕ (see Fig. 1). The agent in this scope is said to be having its turn and is being rewarded. A spatial position of the b-th agent at time-step t is represented by $Pos_b(t)$. This is compared with the a-th agent's prediction value $Pos_{a\to b}$. Therefore the squared difference (Eq.(11)) evaluates the precision of the a-th agent's prediction.

$$F_a = s_1 \times F_a^{turn} + s_2 \times F_a^{predict}, \tag{7}$$

$$F_a^{turn} = \frac{1}{P}\sum^{P}\left(\sum_t^T g_a\left(t\right) \times \sum_t^T g_b\left(t\right)\right), \tag{8}$$

$$g_a(t) = \left\{\begin{array}{l} 1\ Pos_a(t) \in RS_b(t) \\ 0\ Pos_a(t) \notin RS_b(t) \end{array}\right\}, \tag{9}$$

$$F_a^{predict} = -\frac{1}{P}\sum^{P}\left(\sum_t^T P_a\left(t\right) \times \sum_t^T P_b\left(t\right)\right), \tag{10}$$

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

The performance of turn-taking is evaluated for different lengths of time ($T = 500, 1000$ and 1500), 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 certain mutation rates. The GA proceeds by repeating this procedure and the recurrent neural networks evolve.

Noise: Note that sensory noises are added to the input neurons during each run. Therefore agents have to take turns under a noisy environment.

4 Simulation results

4.1 Dynamics Repertoire

Simulation was done with a GA using 15 individuals ($P = 15, E = 4$). Figure 3 shows examples of the spatial trails of an agent from different GA generations with different initial population structures.

We can approximately classify these trails into two patterns based on their appearance. When spatial trails consist of regular curves and the turns are exchanged almost periodically (which corresponds to an abrupt turning point),

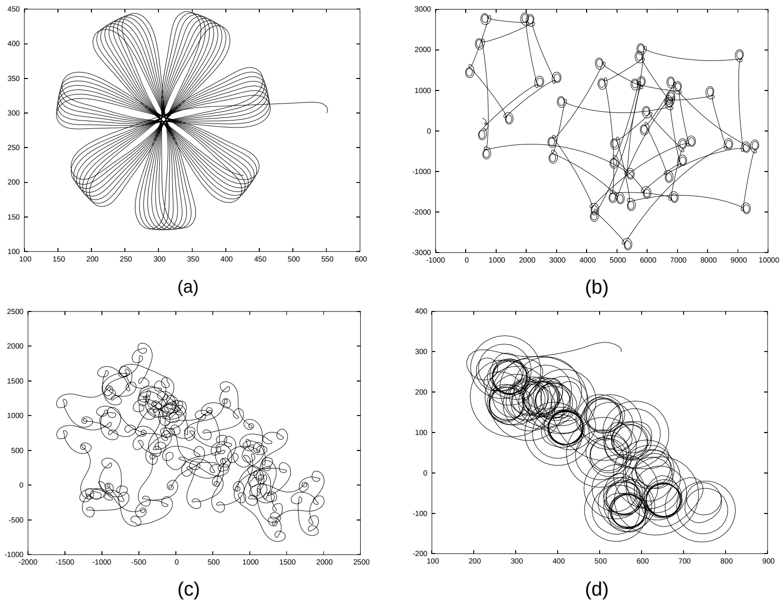

Fig. 3. Spatial trails of turn-taking behaviour observed in the simulations. In order to clarify the qualitative difference of turn-taking structures, a spatial trail of only one of two agents is shown. The other agent moves around these trails generating almost similar trails. All games in these graphs are started from (550, 300). (a) is a example of geometric turn-taking. (b),(c) and (d) are examples of chaotic turn-taking behaviour.

we call them *geometrical* turn-taking. On the other hand, if spatial trails have irregular curves with non-periodic turn-taking, we call them *chaotic* turn-taking.

In the earlier GA generations, the agents with geometric turn-taking have a higher performance (Fig. 3(a)). 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 original pattern. A series of behaviour patterns repeats almost periodically, and in this way the context nodes are periodically activated.

In the later GA generations, more chaotic patterns emerge (Fig. 3 (b), (c) and (d)). In contrast to the geometrical patterns, the turns are exchanged in different places with irregular time intervals. Therefore, the spatio-temporal pattern becomes chaotic. The corresponding context space plots show some tangled continuous-line formations.

The evolution of geometrical turn-takings to chaotic turn-taking is explained as follows: The evolutionary pressure of GA at first makes agents behave in a stable way in the noisy environment. We believe that robustness against noise prefers geometrical turn-taking.

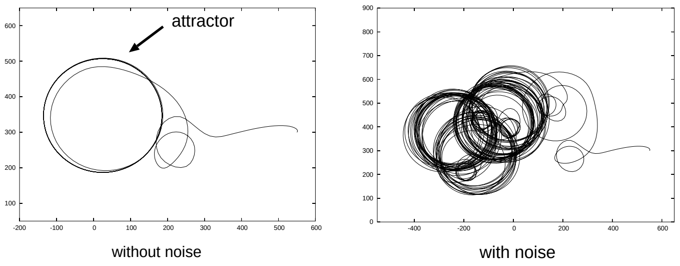

Fig. 4. Noise-driven turn-taking behaviour. There is an attractor of role-fixed behaviour. By adding noise to the agents, an agent can slip out of the attractor and successfully perform turn-taking.

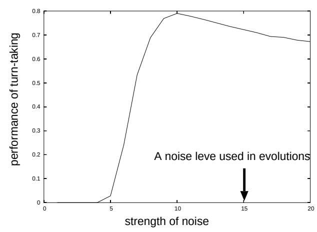

Fig. 5. The performance of turn-taking behaviour as a function of noise strength. Under the lower level of noise, agents cannot perform turn-taking. Beyond a certain noise level, agents take advantage of noise to perform turn-taking. This critical noise level is lower than the one used in evolution.

4.2 Noise-driven Turn-taking

Some turn-taking behaviours are established by taking advantage of the noise (Fig. 4). As shown in the figure, there is a strong attractor of a circular pattern of role-fixed chasing and evading without exchanging turns. Turn-taking emerges beyond a certain noise level (Fig. 5). Below that level, the attractor of the fixed role is too stable to escape. In another case, there are three attractors without noise. One is that agent A chases the rear side of agent B closely. Another one is the opposite, and the last one is that in which both agents chase each other. Every 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-driven behaviours, chaotic turn-takers can establish turn-taking behaviour without noise. Even if noise is introduced into the system, chaotic turn-takers can establish turn-taking behaviours independent of small noises. Namely, they do not utilize noise but suppress the effect of noise to perform turn-taking. On the other hand, noise-driven turn-takers need noise to perfrom turn-taking.

In the next section, we discuss this dynamic adaptability.

4.3 Turn-taking with Virtual Agents

A difference between mere oscillator entrainments and dynamic coupling is found in the 'adaptability' of the coupling between the agents that is established by evolution. In order to clarify the nature of the dynamic interactions more concretely, we compare the behaviour of "live interaction" with "recoded 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 select the two best agents, A and B, from each population. Turn-taking between these agents is studied without introducing noise. This is what we term 'live interaction'. The trails of the agents are 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 a 'recorded interaction'. We perturb the recorded trail and simulate the changes in the turn-taking dynamics.

Figure 6 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 is observed. The behaviours are similar as is shown in the figure. However, a small noise is amplified and the orbit drastically changes from the original orbit around 800 time-steps. In terms of the turn-taking behaviours, the adaptive agent cannot recover harmonization with the perturbed virtual agent any longer. The agent approaches the trail and tries to dynamically resume the original turn-taking behaviour.

Another example (the agents at 3,000 generations) is shown in Fig. 6 (b). These agents establish geometric turn-taking. In this case, agents can adequately cope with the perturbed virtual agent. Note that agents constructing geometric turn-taking behaviour do not always, but frequently do, have a tendency to cope with a perturbed virtual agent. It depends on the timing and strength of the perturbation. Sometimes turn-taking behaviour breaks down when additional noise is added to the recorded trail. However, there are some examples in which turn-taking recovers after a certain period of discrepancy.

5 Discussion

It is found in the experiments of turn-taking against virtual agents, that chaotic turn-takers are much more sensitive to the difference between the live and recorded inputs. In other words, turn-taking is driven by the ongoing interaction. On the other hand, geometric turn-takers are robust against the difference due to the restricted number of dynamics (may be only one or two). Therefore, turn-taking is driven by the stiffness of the individual dynamics. This is also confirmed by the experiments with different noise structures (Fig. 7) and also by the fact that chaotic turn-taking takes over from the geometrical turn-taking in the evolutionary context of our GA simulations. We speculate that geometric turn-takers can take turns only with fewer agents than the chaotic turn-takers. In summary, we claim that the chaotic turn-taking is less robust against noise but has more adaptability, compared with the geometric turn-taking.

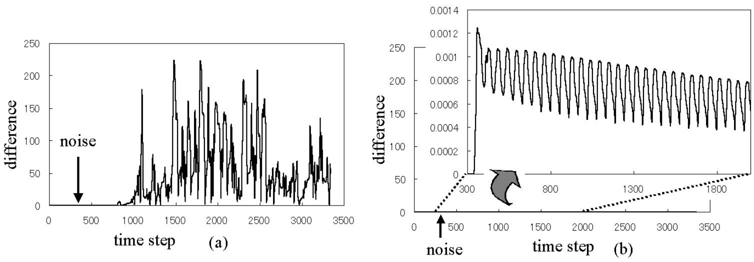

Fig. 6. Differences of orbits between agent's trails in a game with an adaptive agent and with the recorded trail. A small noise is introduced at 340 time-steps. If there is no noise, no difference is observed. Agents used in (a) and (b) correspond to those in Fig. 3 (c) and (a), respectively. The difference is amplified if agents fail to establish turn-taking.

We compare this simulation result with Trevarthen's double-monitor experiments between a baby-infant and its mother [12]. Mother and baby-infant only communicate through videos that display their faces to each other. It is reported that for the baby-infant to engage with the mother, the 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. This is also true for the mother when she watches the recorded video of the baby-infant.

Trevarthen's experiments show that it is not necessarily important for the baby-infant that the mother is displayed on the monitor. It can be assumed that the most important clue under 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. In our simulations, when an agent calculates outputs, this calculation simultaneously affects the internal dynamics. That is, the actions performed form its internal dynamics much as actions form anticipations in the statement above. The agent receives inputs as a partner's actions reflecting the agent's own actions. We maintain that turn-taking is established when these structures are mutually organized. Turn-taking is thus broken in the simulation with virtual agents. We therefore claim that this mutual adaptive coupling of actions and internal dynamics between agents is related to intersubjectivity.

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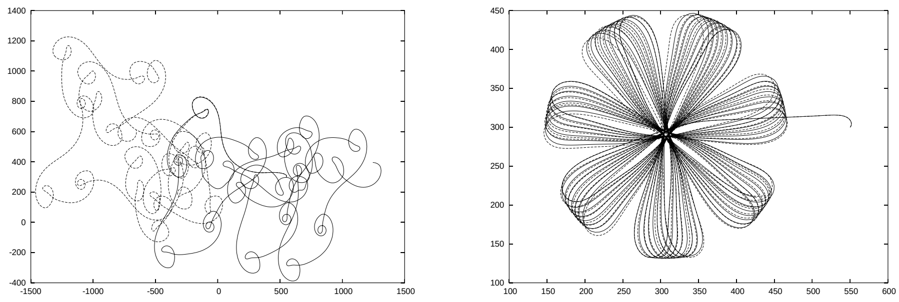
References

1. Cliff, D., Miller, G.F.: Co-evolution of Pursuit and Evasion II: Simulation Methods and Results. From Animals to Animats 4:Proceedings of the Fourth International



(a) (b)

Fig. 7. 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-taking (b) geometric turn-taking

Conference on Simulation of Adaptive Behavior (SAB96), MIT Press Bradford Books (1996) 506–515

2. Dautenhahn, K.: Embodiment and Interaction in Socially Intelligent Life-Like Agents. Springer Lecture Notes in Artificial Intelligence Volume 1562 Springer (1999) 102–142
3. Di Paolo, E.A.: Behavioral coordination, structural congruence and entrainment in a simulation of acoustically coupled agents. Adaptive Behavior 8:1 (2000) 25–46
4. Ikegami, T., Taiji, M.: Structures of Possible Worlds in a Game of Players with Internal Models. Acta Polytechnica Scandinavica Ma. 91 (1998) 283–292
5. Ikegami, T., Taiji, M.: Imitation and Cooperation in Coupled Dynamical Recognizers. Advances in Artificial Life, Springer-Verlag (1999) 545–554
6. Ikegami, T., Morimoto, G.: Chaotic Itinerancy in Coupled Dynamical Recognizers. (submitted to Journal of American Institute of Physics)
7. Ikegami, T., Iizuka, H.: Joint Attention and Dynamics Repertoire in Coupled Dynamical Recognizers. The Proceedings of Imitation in Animals and Artifacts II (2003)
8. Iizuka, H., Ikegami, T.: Simulating Turn-taking Behaviours with Coupled Dynamical Recognizers. The Proceedings of Artificial Life 8, Standish et al.(eds), MIT Press (2002) 319–328
9. Reynolds, C.W.: Competition, Co-evolution and the Game of Tag. Artificial Life IV, Brooks & Maes (eds), MIT Press (1995) 59–69
10. Scassellati, B.: Imitation and Mechanisms of Joint Attention: A Developmental Structure for Building Social Skills on a Humanoid Robot. Computation for Metaphors, Analogy and Agents, Vol. 1562 of Springer Lecture Notes in Artificial Intelligence, Springer-Verlag (1999)
11. Trevarthen, C.: Descriptive Analyses of Infant Communicative Behaviour. In: Studies in Mother-Infant Interaction, H.R. Schaffer (ed.), London: Academic Press (1977)
12. Trevarthen, C.: The Self Born in Intersubjectivity: The Psychology of an Infant Communicating. The Perceived Self, U. Neisser(ed.), Cambridge University Press (1993) 121–173