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RESEARCH ARTICLE

Anticipatory behavior in virtual universe, application to a virtual juggler

C. Buche* and P. De Loor

UEB/ENIB/LAB-STICC, CERV-25 rue Claude Chappe, F-29280 Plouzané, France

ABSTRACT

To be believable, virtual entities must be equipped with the ability to anticipate, that is, to predict the behavior of other entities and the subsequent consequences on the environment. For that purpose, we propose an original approach where the entity possesses an autonomous world of simulation within simulation, in which it can simulate itself (with its own model of behavior) and simulate the environment (with the representation of the behaviors of the other entities). This principle is illustrated by the development of an artificial juggler in 3D. In this application, the juggler predicts the motion of the balls in the air and uses its predictions to coordinate its own behavior to continue to juggle. Copyright © 2012 John Wiley & Sons, Ltd.

KEYWORDS

anticipation; real-time interaction; decision making; behavioral model; virtual juggler; virtual character; computer animation

***Correspondence**

C. Buche, UEB/ENIB/LAB-STICC, CERV-25 rue Claude Chappe, F-29280 Plouzané, France.
E-mail: buche@enib.fr

1. INTRODUCTION

Automatic decision making by artificial systems situated within given environments is difficult to model, especially when the environment is dynamic, complex, open, and populated with independent entities. Virtual reality is an ideal field for modeling complex decision-making behavior, as it occurs at the heart of interactions with humans, who elicit subtle and varied reactions and perceptions. The emergence of interactive motion systems (Wiimote, Kinect, etc.) makes studying the subtlety of these connections even more crucial. Graphical realism is not sufficient and indeed is no longer the priority: the reactions and thus real-time decision making by the virtual entities within the environments must be "believable" [1]. This notion of believability is subtle and varied and can be studied according to many different criteria. For example, there are studies relating to movement [2], to the character's realism [3], and to the impact of the synchronization between image, sound, and movement [4]. We, however, are interested in the believability of a behavior "during a behavioral interaction" [5] and, more exactly, in the ability to anticipate more or less precisely the future of the environment thanks to the knowledge of its dynamic properties as humans do. We do not address graphical realism nor gesture synthesis. Our work focuses on the perception-based decision-making dynamic. In this research, we consider only believable as *giving the illusion of being controlled by a human*.

Anticipation can be observed in living creatures at almost every stage of evolution (including bacteria, cells, plants, vertebrates, and mammals). As an illustration of this principle, the "waiter experiment" [6,7] gives the example of a waiter holding a tray in one hand, on which is balanced a jug of water. With his other hand, the waiter lifts the jug. At that moment, the hand holding the tray, which should have lifted as it is now carrying less weight, remains in the same position. Instinctively, the waiter predicts the consequences of his movement, **anticipating** the relief of the load-bearing arm [8].

Surprisingly, despite increasing (or even omnipresent) proof of its importance, anticipation has for a long time been ignored or underestimated in the behavioral modeling of virtual entities. Implicitly, planning architectures make some anticipations but they are based on representations that are difficult—if impossible—to define as the environment evolves according to different aspects or different scales (apparition or disappearance of objects or actors, modification of their trajectories, new behavior to discover...). Psychology [9,10] and neurology [11,12] stress the importance of our anticipation mechanisms in reasoning. They also point to the use of *internal behavioral simulations* in the lead-up to effective reasoning [8].

This notion of internal behavioral simulation could be used to overcome the problem of symbolic representation in classical artificial intelligence reasoning generally based on the notion of "theory of mind.'. Indeed, if we *simulate* the world, we can have an approximation of its future without the need of a logical representation based on symbols and inference rules. Thanks to virtual reality, the world could become its own model, as Brooks proposed to do for artificial intelligence [13].

As this behavior-modeling paradigm is relatively new, it remains unconfirmed as there are still many questions regarding its use, functioning, and success. This document addresses these questions by proposing to model anticipation as an internal simulation of the evolution of the environment and of the interactions between the autonomous entity and that environment. Internal simulation is thus taken into account during the decision-making process.

This article begins by presenting the theoretical framework of anticipation in decision making. We then go on to examine the use of internal behavioral simulation in integrating the anticipatory process into an artificial entity's decision-making process. Next, we describe our application, in which a virtual juggler anticipates the trajectory of balls in a simulated model and subsequently controls the position of its hands. We then evaluate the impact of anticipation on the virtual juggler's decision-making processes. Finally, we present our conclusions and the future direction our study will take.

This paper extends our first study presented in the conference Computer Animation and Social Agent (CASA'11) [5]. In this new contribution, we develop the theoretical part starting by the foundation of anticipation to our proposal. In addition, we present new experiments showing new results concerning the learning process, the robustness of our model, and the link between anticipation and decision making.

2. THEORETICAL FRAMEWORK: THE ROLE OF ANTICIPATION IN DECISION MAKING

In this section, we present the theoretical framework. The aim is to recall the foundations of anticipation, which leads us to concern with the principle of *internal simulation*. Then, we emphasize the importance of an explicit model of anticipation.

2.1. The Foundations of Anticipation

As our aim is to simulate human-like behaviors, it is important to have a look at previous research in different fields of cognitive science such as philosophy, psychology, neurology, and physiology.

2.1.1. Philosophy: Man Is Oriented toward His Future.

The first people to study human behavior were philosophers. These studies showed that Man, by his very nature, is oriented toward the future, questioning his future. Philosophers suggest two approaches: (i) the use of past knowledge in anticipating the future [14,15], an idea which is also prevalent in psychology; and (ii) the theory of simulation [16,17], which is also prevalent in neurology and physiology.

2.1.2. Psychology: The Role of Past Knowledge in Anticipating the Future.

This idea suggests that we use the memories of our past experiences and observations to anticipate the consequences of our actions and the behavior of those around us. Identifying regularly observed phenomena from the past enables us to react in an anticipatory manner. This idea opened the door to anticipation studies in behavioral psychology. Studies on rats led to the identification of anticipatory mechanisms [18] and the use of predictive models† of the environment [19]. Studies with human subjects revealed the importance of anticipation in human behavior [20,21]. Hoffman thus put forward a behavioral model (anticipatory behavioral control), basing his work on the ideomotor principle‡ [22]. Anticipatory behavioral control is a theoretical decision-making and learning model in which the subject first focuses on the desired outcome and then takes the context into account to choose a suitable action.

2.1.3. Neurology and Physiology: Simulation Theory.

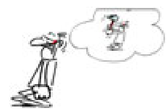
For this field, the brain is a simulator for actions, and thought is the simulated interaction with the environment [8,12,23]. It was also a precursor to all anticipation studies. Cerebral imaging techniques in neurology have enabled us to measure cerebral activity at the heart of a monkey or a human's brain while carrying out certain actions. It was possible to use the results of such tests to isolate an area of the brain known as mirror neurons [11]. These neurons are activated in very similar ways in the situations described in Table I. Although all these elements are still hotly debated topics in cognitive science, they led some researchers to suggest that this area of the brain might enable the mental simulation of actions and the anticipation of others' behavior *via* an empathy mechanism.

Internal simulation, particularly of movement, has foundations in neurophysiology, which are now well documented [24]. Individuals do not make these sensorimotor predictions through logical reasoning based on abstract symbols representing the real world [25]. Instead, they are made via biological simulation where, thanks to inhibiting mechanisms, "everything occurs as if" the individuals were really acting [8]. For vision, for example, the brain

†Predictive models suggest potential outcomes, thus defining the anticipation process.

‡The ideomotor principle suggests that actions are chosen according to the desired outcomes rather than as a reaction to a stimulus.

Table I. Situations “showing" the mental simulation of actions and the anticipation of others’ behavior in the brain.

Carrying out an action	
Imagining carrying out the same action	
Watching a third person carrying out the same action	
Imagining or anticipating a third person carrying out the same action	

has a way of imagining eye movements without moving thanks to the action of inhibiting neurons, which close the command circuit of the ocular muscles: by staring at a spot in front of you and by moving one’s attention, one has the impression of looking around the room, a sort of “interior regard". This virtual eye moment is simulated by the brain activating the same neurons, except that the action of the motor neurons has been inhibited. The brain can thus be considered a *biological simulator* [8] that is able to make predictions based on memory and to create hypotheses based on internal models of the phenomenon.

Following this idea, in this article, we propose a model to predict, not by formal reasoning but by behavior simulation. The next step is to explore anticipation models.

2.2. The Importance of an Explicit Anticipation Model

In this section, we wonder how an explicit modeling of an anticipation mechanism might benefit our research. To better understand our position, we need to clearly differentiate implicit and explicit anticipation models.

2.2.1. Implicit Anticipation Model.

In the first case, implicit anticipation does not rely on specific predictive models to anticipate the future; obtaining knowledge about the future is part of the decision-making mechanism or of genetic information. One example of low-level implicit anticipation is that of trees that shed their leaves in autumn to avoid frost damage in winter. As temperatures drop and days become shorter in autumn, the trees anticipate the arrival of winter and duly react by shedding their leaves, breaking the connection at the inside of the leaf stems (so that the leaves can then be carried away by the wind). It is likely that the tree does not use an explicit environmental model to predict the coming of winter but rather genetically transmitted implicit anticipation. The same anticipatory mechanisms can be observed in hibernating animals.

2.2.2. Explicit Anticipation Model.

In the second case, explicit anticipation uses one or more explicit predictive models of the environment and/or self and uses these models to make predictions about the future. An example compares the hunting behavior of a dog with that of a snake [26]. It has been observed that dogs go on chasing prey even if they can no longer see it by using a predictive prey model, thus predicting its behavior and continuing with the hunt. However, when snakes lose sight of their prey, they cannot predict their movements or future positions and instead anticipate (implicitly) that they have more chance of catching their prey by returning to the place where they last saw it. According to Rosen, human behavior is essentially anticipatory and is based on explicit environmental models [27]. He offered the example of a hunter who finds himself a few meters away from a bear and whose behavior would be to hide so as not to be seen. It is not the sight of the bear itself that triggers this reaction but rather that which the hunter imagines, or anticipates, might happen as a result of an encounter with a bear.

2.2.3. Conclusions.

From these examples, it would seem that complex cognitive behaviors (of humans and intelligent animals) rely on explicit predictive models used to anticipate their environment, whereas less complex cognitive behaviors do not.

Whatever the complexity of the behavior is, using an explicit anticipatory model is a means to handle its subtlety when it is a question of its simulation. Moreover, studying in detail the inherent mechanisms implied in anticipation at different cognitive levels (reactive or deliberative) gives cues to better take into account the *effects* of anticipation,

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i.e. its consequence on the successes but also on the failures of different tasks in different contexts.

Consequently, the next step is to explore existing proposals integrating an explicit model of anticipation.

2.3. Anticipation-Based Artificial Behavior

According to [28], there are three categories of explicit anticipation :

1. The anticipation of considerations, which brings together approaches using predictions about the possible *rewards of the potential actions*. In this category, we find all the reinforcement learning algorithms, Q-learning [29], Sarsa [30], and classifiers systems [31].
2. Sensory anticipation includes the use of predictive environmental models to *orient the entities' perceptions* more effectively, especially to process expected rather than sudden perceptions [24]. This approach brings together the ideas of active perception, attention, and sensory blindness. A good example of this is the experiment by Simon and Chabris, which asked students to watch a basketball match on television and to count the number of passes between players [32]. Almost all of the students gave the correct answer. However, the majority failed to notice the man dressed as a gorilla who walked into view, stopping to beat his fists against his chest.
3. State anticipation deals with the use of predictive models to *foresee evolutions in the environment* to observe how this is taken into account in decision making. In this category, we find all algorithms with the ability to recognize patterns and to make predictions from those patterns (for instance, the Hierarchical Temporal Memory (HTM) architecture [33]). Virtual entities could use this knowledge to act in goal-oriented anticipation (planning), that is, to try to detect these unwanted states in the environment before they occur and thus react so that they might be avoided [34].

It must be noted that state anticipation can also include anticipation of considerations and sensory anticipation and as a consequence seems especially interesting. It has been the focus of a great deal of research [34–38]. These studies raise the following questions:

- In what circumstances are anticipatory behaviors the most believable and lead to faster adaptation than non-anticipatory processes?
- What is the link between immediate decision making and the anticipatory mechanism?
- What are the links between anticipation and learning?

The goal of this paper is to give clues to these questions. First, we propose an anticipatory architecture model. Next, we show its application to a virtual juggler. Finally, we evaluate the anticipatory mechanism, its qualities, and its impact on decision making for the juggler animation. It

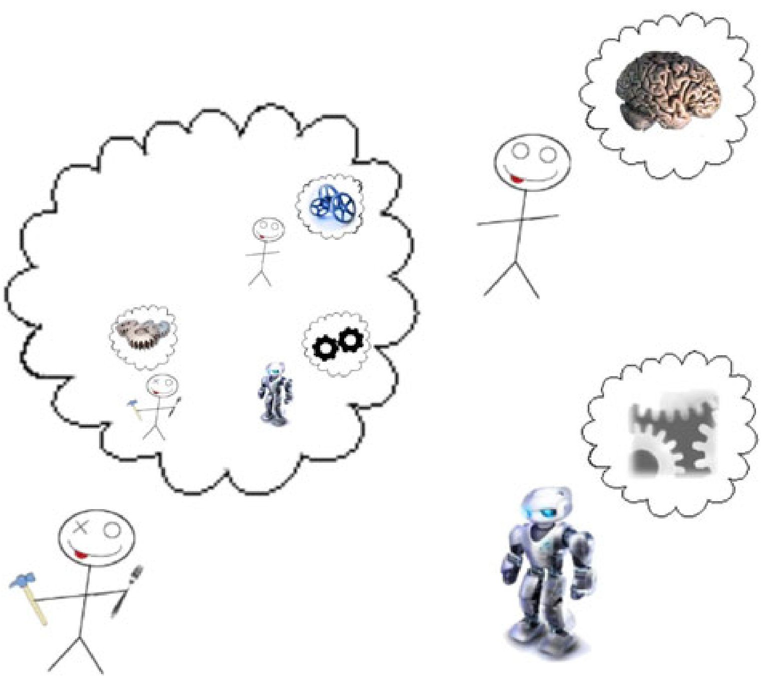

Figure 1. The entity (left) anticipates the behavior of the other entities (right). To do so, it possesses an imaginary world in which it "imagines" what is going to happen.

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must be noted that the virtual juggler is just an application to test our predictive model.

3. PROPOSAL: CONCEPTUAL FRAMEWORK

Our proposal is based on the theory of internal simulation with explicit anticipatory representation, that is, advance simulation of the evolution of the entity's environment (state representation) to make a decision. To do so, we propose to populate a virtual world with our virtual entities with the ability to predict and the ability to learn. The aim is to create an explicit anticipatory model; the most important issue is to achieve a final behavior that accounts for the characteristics of believability and adaptation.

Research in cognitive ergonomics have shown the existence of several cognitive levels operating in parallel during the execution of tasks aiming at path planning by humans [39]. The first two levels may correspond to the modes of control for acting and predicting. The third level, more abstract, is the place for questioning and learning.

Inspired by these ideas from cognitive ergonomics and neurophysiology, we propose an architecture for the implementation of an autonomous virtual actor, predictive and adaptive. Three cognitive processes operate in parallel and are synchronized using messages. The first, reactive, operates at high frequency for the acquisition of certain sensors and is associated with sensorimotor strategy. The second, predictive, conducts internal simulations with medium frequency, which can be synchronized periodically with perceptual information. This predictive mode can change the reactive mode by providing a new sensorimotor strategy. The third, adaptive, compares predictions with perceptions to change behavior patterns used by the other two modes. Implemented when a prediction error is obvious, the third mode can operate in the background at low frequency. The next sections describe levels 2 and 3.

3.1. Virtual Actors and Imaginary Worlds

While acting within the virtual world, each entity can simulate its own behavior in its imaginary world (with its own behavioral model), along with that of its environment (using the representation that it has of the behavior of other entities). This simulation occurs a phase ahead of the original simulation, enabling the entities to make predictions. This imaginary space, unique to each entity, functions in parallel with its activity within the virtual world, asynchronously so as not to block the behavioral animation (Figure 1). This imaginary world is a universe of a *simulation within a simulation*.

3.2. Virtual Actors and Learning

Prediction in the imaginary word implies a representation of this world and of its dynamic. To obtain this representation can be a hard challenge because a world adapted to this approach is open: unpredictable interactions can appear every time, and moreover, the dynamic properties can be disturbed (for instance, wind can disrupt the trajectories of flying objects). So, learning mechanisms are a good way to learn the dynamics of the world.

In our proposal, predictions in the imaginary world are improved by observing the virtual world online. The virtual actor will then modify its representations of other entities using a learning mechanism. It must be noted that this observed world can also be populated with other actors or with human-controlled avatars [40]. Similarly, for the approach to be generic, it is important for the control of the behavioral model to be independent of the learning mechanism so that the model might be piloted by any decisional mechanism.

The development of learning adds a whole extra dimension to our model (Figure 2). Indeed, our virtual entities evolve in a virtual world (first dimension: the virtual world), simulate the representation of behaviors in an imaginary world (second dimension: the imaginary world), and adapt the representation of behaviors through learning (third dimension: the abstract world).

3.3. Links between Virtual, Imaginary, and Abstract Worlds

The challenge here is therefore to identify the three dimensions and to understand their interactions. The three worlds

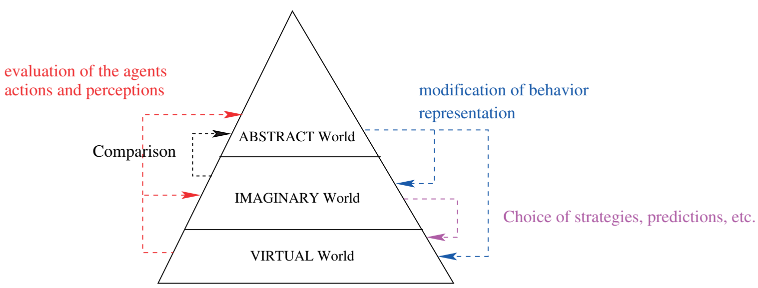

Figure 2. Conceptual framework: representation of the entities' three dimensions (the real world, the imaginary world, and the abstract world).

evolve in parallel and correspond to three different levels of abstraction. Nevertheless, they are all related and share information. The virtual world provides the necessary information to the imaginary world to simulate an approximate representation of the virtual world. Furthermore, it provides the abstract world with the information it needs on the model, that is, an approximation of these effectors and the sensors linked to the models to be adapted. The imaginary world feeds back information, particularly concerning the choice of strategies or predictions (Figure 3).

4. APPLICATION: JABU

The first implementation of this approach is a virtual juggler that predicts the displacement of balls in the air to coordinate its movements and juggle successfully.

The choice to perform an anticipatory juggler comes from the nature of the juggling task, which is highly dynamic and where the anticipation is essential. Indeed, unless you can move your hands instantly from one place to another, it is necessary to predict the behavior of balls to react quickly enough to keep the juggling activity with high temporal constraint (a small delay causes the fall to the ground of one or more balls).

The problem of a virtual juggler was discussed by [41,42], but these approaches have not taken into account the modeling of generalized anticipation or the theory of simulation. More generally, they do not address the links between cognitive sciences and a character's behavior. We will show that the conceptual framework proposed here can account for adaptation but also plausible errors, through interactions more or less predictable, especially with a real human. An application of the conceptual framework of anticipation for this example is shown in Figure 4. The application is called JABU: juggler with anticipatory behavior in a virtual universe (Figure 5).

The virtual world of the juggler has physical properties (inertia, gravity, wind, etc.) through the use of a physics engine, the Open Dynamic Engine (http://www.ode.org/). Of course, these quantities are not explicit in the model of control. This control is adjusted through an attentional process focused on the *next* (anticipated) ball (at this time

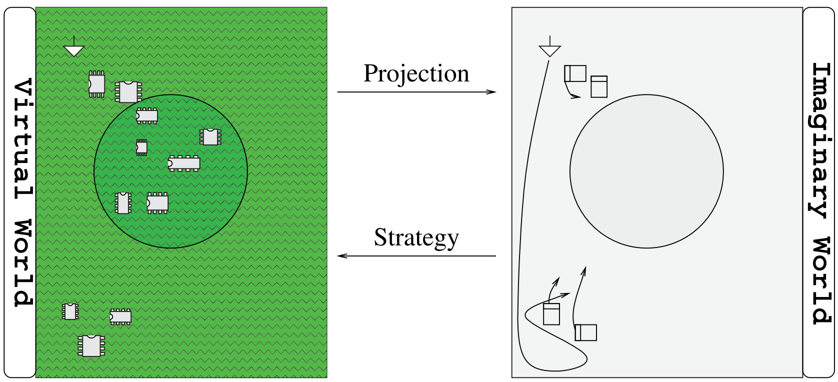

Figure 3. Internal behavior simulation. The actor, represented by the triangle, establishes a simplified representation of the world. It simulates both its own behavior and that of the other entities in an imaginary world. After simulating a number of different possibilities, it can decide which strategy to adopt.

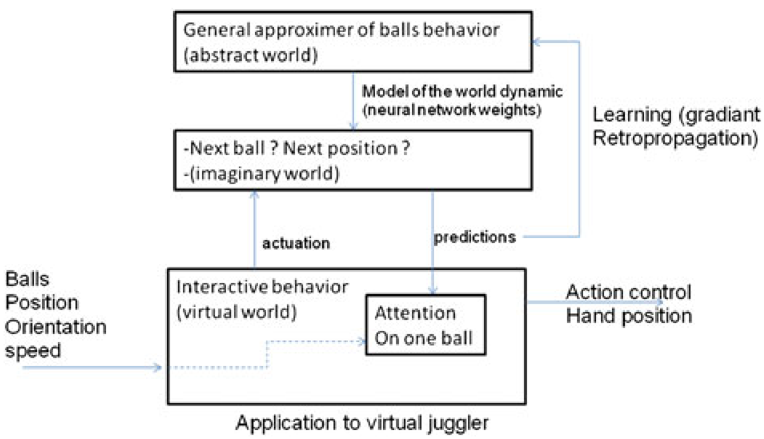

Figure 4. Instantiation of our framework for a virtual juggler.

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Figure 5. Screenshots of the JABU application.

one ball by hand). The approximate position of the balls is made by their simulation in the imaginary world of juggling. Function approximation properties of this imaginary world come from different neural networks (NN). The abstract world corresponds to the weights of the arcs of these networks. Because they are universal approximators, we will see that they allow real-time adaptation of the juggler gestures to different types of disturbances. In the following, we clarify the implementation of these principles.

4.1. Virtual World

4.1.1. Presentation.

The motor behavior of the juggler is controlled by its hands. The hands have independent functions, that is to say that there are no complex juggling moves or tricks but simply a succession of catches and throws of the balls, where each movement is independent of the others. As soon as a ball “arrives” at the same height as the hands, it must be caught and rethrown. The time taken for a hand to move is not negligible and exposes the juggler to a risk of delay and thus “missing" the ball, which is also amplified by prediction errors. As mentioned earlier, the precise reproduction of the movement is not our priority, and the hand’s movement time is an empirically adjustable variable that reflects the delay between the decision being made and the action being carried out. In the following section, for simplicity’s sake and to keep things brief, when we refer to a hand’s activity, we also of course mean that the theoretical model has been implemented for the anticipatory decision making applied to our juggler.

The different phases of juggling are the following. The juggler begins by looking for a ball in the air. Once the ball is spotted, the hand must aim at an estimated reception point (prediction T1). Then, it is possible to refine this reception point. To do so, the hand must estimate and correct the anticipated trajectory of the target ball (prediction T2), which is the *object of attention*. Each hand will therefore be able to catch or miss the target ball. If the ball is caught, the juggler will be able to throw it in the air. Whether the ball is caught or missed, the hand again begins to look for a ball in the air.

4.1.2. The Link between the Virtual and Imaginary Worlds.

To aim at a reception point and to estimate the anticipated trajectory of the target ball, the hand will have to use predictive models. Within the context of juggling, information must be gathered quickly to maintain the juggling dynamic. The use of perceptron-type NN to make predictions about the trajectory is adequate. Indeed, NN are executed rapidly, and online learning occurs both quickly and effectively. Furthermore, NN correspond to our need to manipulate (both spatial and temporal) digital data. It is, of course, also possible to use determinist equation models of movement to make predictions. However, such precise predictions would be extremely noise sensitive (disruption of the environment as the ball falls) and would not account for the use of approximations and readjustments in real time, which seem to be the basis of the anticipatory mechanisms that we aim to respect [8].

Table II. Input/output of neural network T1.

Inputs	Output	Parameter	Objectives
V_x	Δt	h	Temporal classification
V_y	Δx		Vague spatial prediction
V_z	Δy		

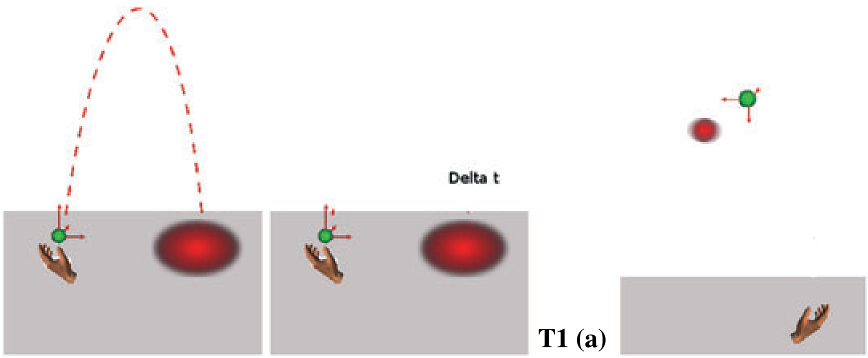

Figure 6. **NN T1**: The ball has just been thrown at a speed in x, y, z (arrows), giving us a first estimate of the position at which it will cross plane $z = h$ (blurred circle) and how long this will take (a). **NN T2**: At any given time as the ball falls (ball with arrows), we can use its speed (arrows) to make a more accurate estimation of its position in Δt seconds (blurred ball) (b).

It must also be noted that we are working from a pragmatic rather than a neurophysiological perspective. In no way do we suggest that we are simulating "low-level" neural functioning like that in robotics [43] but rather that we are creating an anticipatory behavior that is as effective as possible. Thus, perception must be seen as a simple approximation. It must also be noted that NN are in this case used as explicit models of anticipation rather than functioning: NN outputs are information concerning next positions (category 3: evolutions in the environment).

We shall now go on to describe the predictive models used for simple juggling (juggle alone) and for juggling between a virtual entity and a human user.

4.2. Imaginary World

This section describes the juggler's predictions T1 and T2.

4.2.1. Prioritizing the Balls (T1).

The NN T1 will provide us with the estimated temporal and spatial data for each ball at the moment it is thrown. These data will be used to categorize the balls and attribute them priorities, thus triggering the attentional process on the priority ball. The data required to calculate these estimations are the current speed of the ball and the height h at which the ball must be caught. This NN includes the following:

- Three inputs: the three speed components of the ball in 3D representing the three axis of the space
- Three outputs:
  1. The estimated time (duration) before the ball crosses a plane in $z = h$ (h determined during learning)
  2. The movement in x of the ball on crossing plane $z = h$
  3. the movement in y of the ball on crossing plane $z = h$

x and y define the Cartesian plane. The data used by the NN T1 are summarized in Table II. The information that it represents is illustrated in Figure 6.

This prediction enables the juggler to choose the next ball to catch and to focus on it. Having made this decision, the juggler begins to move its hand toward the estimated area while at the same time refining the prediction using a second, more "accurate", predictive model, which will enable it to anticipate the movement of the ball more precisely in a shorter time (prediction T2; Section 4.2.2).

4.2.2. Refining the prediction of the target ball (T2).

The NN T2 refines the spatial prediction of where a ball will fall as it falls. Information can be obtained at different temporal levels (according to Δt). This NN includes

- Three inputs: the three speed components of the ball in 3D
- Three outputs: an estimation of the movement in x, y and z of the ball after a given time Δt (where Δt is defined during learning)

The data used by the NN T2 are summarized in Table III. The information that it represents is illustrated in Figure 6.

4.3. Interaction between Virtual Jugglers and a Human

The general features of this proposition allow several jugglers to interact together. So that they can do this, the only

Table III. Input/output of NN T2.

Inputs	Output	Parameter	Objectives
Vx	Δx	Δt	Refined spatial predictions
Vy	Δy		
Vz	Δz		

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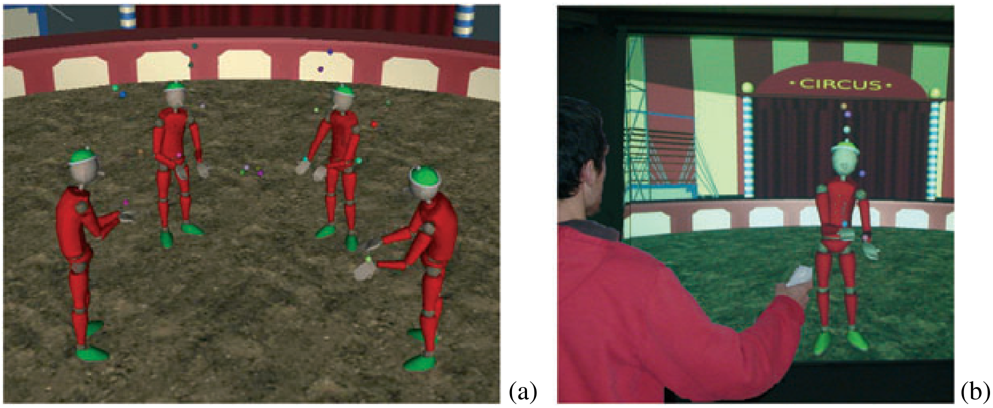

Figure 7. Multi-jugglers (a) and a human can juggle with the virtual juggler using the Wiimote (b).

change is the direction of the ball launched by each juggler (Figure 7 (a)).

Our juggler can also catch a new ball thrown by a human user (Figure 7 (b)). This is extremely pertinent for evaluating the believability of our virtual juggler (real-time decision making, online adaptation, etc.). Introducing a human user also requires the introduction of a new type of prediction (T3). T3 is similar to prediction T1, except that the ball is not thrown by the virtual juggler. The human user interacts with the virtual juggler using a Wiimote (remote game controller from the Nintento Wii console). This peripheral device measures the movements of the human user's hand.

4.4. Abstract World

In its example base, NN T1 has access to throws made by the juggler itself (low speed in x and y) whereas NN T3 records the balls thrown at a distance by a third person (much greater speeds).

4.4.1. Learning.

We chose a topology with two hidden layers as the aim was to approximate a continuous function [44]. Each hidden layer has 19 neurons, and we thus obtain $3\times19\times19\times3$ multilayer perceptrons. We assign the perceptron weights with given values prior to learning. The activation function of the neurons is limited. The learning algorithm is a retropropagation of the gradient error. Learning is thus conducted with a maximum of 100 iterations using the Fast Artificial Neural Network.[§] The parameters to be determined are h for the NN of T1 and Δt for the NN of T2. In our example, $h = 2.5$ cm and $\Delta t = 0.1$ s.

4.4.2. Verification.

We divided the data into two subsets: the learning set and the validation set. The validation set is not used for

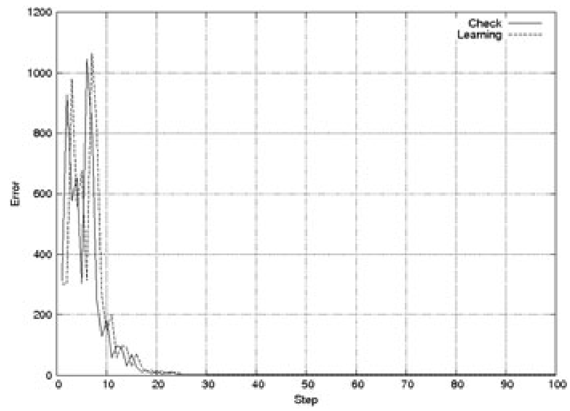

Figure 8. Overall error in learning and validation.

learning but rather to verify the relevance of the network with unknown samples. In this case, we have a sample of 500 pairs of inputs/outputs for NN T1. The learning set uses two-thirds of this sample, and the rest is in the validation set. We obtain Figure 8. The graph illustrates the mean quadratic error at each stage of learning for each sample. It must be noted that the learning set shows that the error decreases dramatically, and the validation set confirms that overlearning does not occur.

5. EVALUATION: THE EFFECTS OF PREDICTION ON BEHAVIOR, AS APPLIED TO JABU

In this section, we shall evaluate the anticipatory mechanism, its qualities, and its impact on decision making and the final result: the juggler animation. The generalization abilities of NN allow the in-line adaption of the juggler's motion to disturbances. The tests presented will vary the initial conditions for a given period. All of the tests include 42 balls thrown towards the virtual juggler (one ball every 0.75 s). We will observe the number of balls dropped by

[§]Fast Artificial Neural Network library available at http://leenissen.dk/fann/

the juggler (i.e., those that fall below the juggler's knees and that it is unable to catch).

5.1. Quality of the Model

Here, we will focus on the quality of our model, enabling us to make predictions about T1 and T2.

First, we compared the performance of our juggler with the spatial and temporal predictions based on our NN and others based on equations of movement. We simultaneously launched ten 1 min NN simulations and 10 others using calculated equations. An average of 30 balls were dropped for the NN and 31 for the equations. We can thus conclude that the prediction of the NN T1/T2 and the equations (exact prediction) are equivalent, so NN are good-quality models for the juggling simulation.

We then attempted to distort the prediction model. To do so, we weighted the input/output data provided for learning according to a maximum error percentage. We compared the performance of our juggler for a distorted T1 prediction with an augmented maximum error percentage (from 0% to 180%) against the original data values. We conducted five simulations for each percentage. The experiment was based on 1 min simulations for each maximum error percentage. We obtained the results presented in Figure 9. The more the input/output data are distorted, the more balls the juggler drops. There is a distinguishable breaking point around the 120% maximum error. This therefore supports the reliability of our T1 prediction.

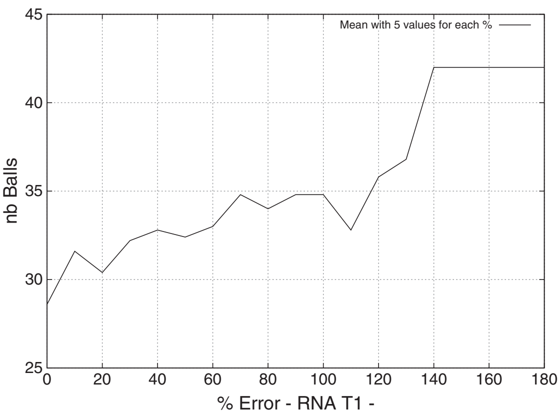

Figure 9. Average number of balls dropped according to the error percentage of the data provided to the NN for the T1 prediction.

5.2. Disturbing the Environment Online

Here, we experiment by distorting the model to validate its reliability. This will be tested by changing the projectile, varying gravity in the virtual environment, and adding wind (Figure 10). This information will not be given to the juggler; its imaginary world and its abstract world will therefore provide different conditions than the virtual world.

First, we introduce jerks in the projectile trajectories because they become maces rather than balls. In this case, the NN T1 is less precise in its prediction, but the NN T2 is able to correct properly the prediction and the juggler continues to juggle when balls are *transformed* in maces.

In Figure 11, we introduced gravity variations: on the y-axis, the number of balls dropped, and in the x-axis, the value of gravity in meter per square second. We calculated the mean for 10 values. The experiment was based on 1-min simulations for each gravity value. We observed that juggling was possible for gravitational values between 6 and 15 (normal gravity: 9.81). In cases of extremely low gravity, no balls were recorded as dropped, as they did not have the time to fall to the ground during the short simulation time.

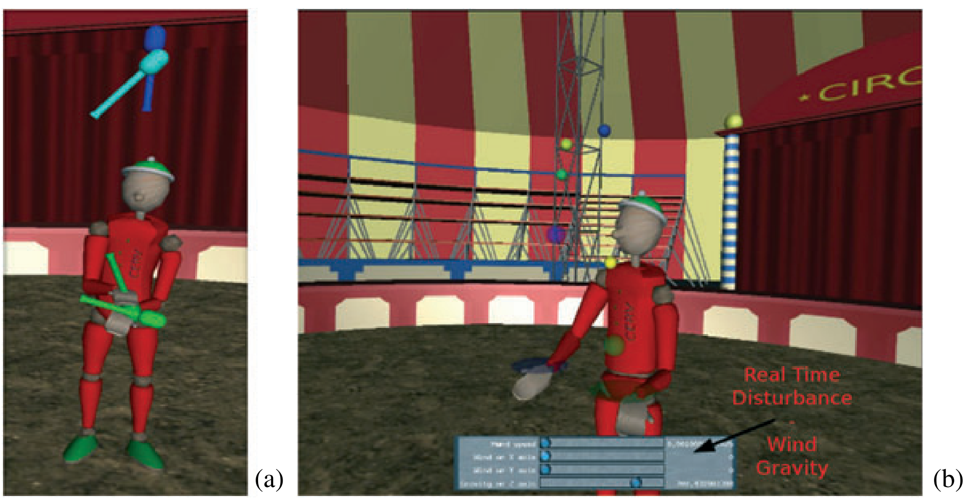

Figure 10. Juggling with maces (a) and disturbing the environment conditions in line (wind, gravity) (b).

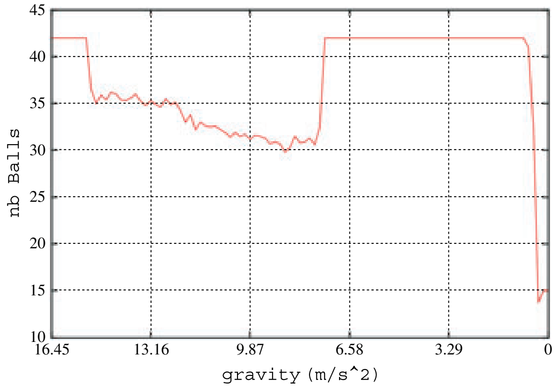

Figure 11. Average number of balls dropped according to gravity.

In Figure 12, wind was added. We thus obtain a curve for dropped balls according to wind in x (a) and in y (b). In the y-axis, we observe the number of balls dropped and in the x-axis the acceleration according to wind speed (in m/s^2, with direction indicated by positivity or negativity). The x-axis value is an acceleration due to the fact that we use a modification of gravity to simulate the wind. The mean was taken for five simulations for each wind value.

For wind in x (width), we observe that between -0.5 and $+0.5$ m/s^2, the juggler catches most of the balls. Beyond that wind speed, it is much more difficult to juggle correctly. For wind in y (depth), the range of speeds in which the juggler continues to juggle correctly is much smaller (between -0.2 and $+0.2$ m/s^2).

5.3. Relationship with Decision Making

The predictive model provides information for decision making, here, the choice of hand movements. We experiment with variations in the execution of the decision-making model for one given predictive model. We decided to vary hand speed. Figure 13 illustrates the evolution of the average number of dropped balls according to varying hand movement speed. For this experiment, we conducted 19 simulations at the same speed. The change in speed took place at 0.0005-s intervals. The speed boundaries varied from 0.0005 to 0.1 s, and the experimental simulation lasted 2 min.

It was observed that beyond 0.04 s, a high percentage of balls were dropped. Despite the anticipatory mechanism, decision making no longer enabled the juggler to juggle successfully. We also noted that the juggler could no longer juggle with more than nine balls at once.

5.4. What Would Be the Behavior of the Juggler without This Anticipation Mechanism?

Now that we have presented these results, it is interesting to come again on the main purpose of our work : improving the credibility of our virtual characters. As mentioned earlier, in our case, this notion of credibility must be seen in terms of interactive behavior and not in terms of realism (such as that in gesture synthesis for example [45,46]). Virtual jugglers were developed in different works by [42] or [41], generally to address the planning problem but rarely the interactive problem, that is, the disruption of the plan at any time and in any direction. For us, the goal is on the reaction of the avatar to different un-represented interactions. Of course, it is quite excessive to affirm that all possible disruptions are possible and that all interactions are un-represented because we know in advance what kind of disruption we will present to the model. Nevertheless, our proposition is a step toward this ideal situation. Anticipation improves the autonomy of our juggler. As an example, the important human-like behavioral properties we choose to highlight and that could not be reached without an explicit anticipative mechanism are the following:

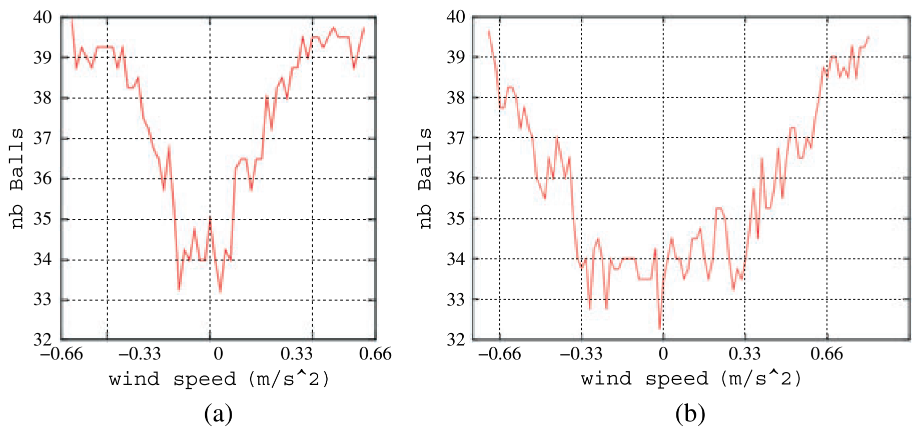

Figure 12. Mean number of dropped balls according to wind speed in y (a) and in x (b).

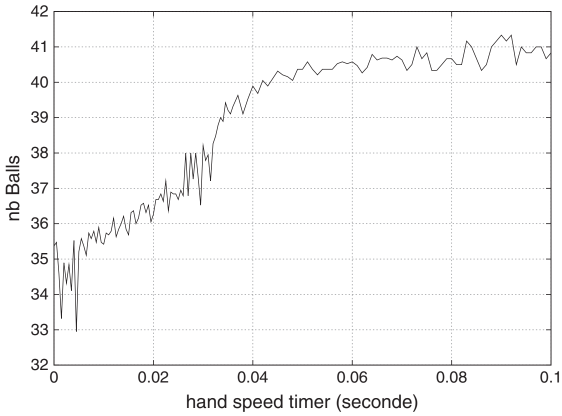

Figure 13. Average number of balls dropped according to hand speed.

- The abilities to focus, during action, on a few number of sensations, depending on the current context of the situation. This attentional mechanism has a drawback: humans can miss an action that could succeed with an optimal calculus. It is exactly the case with our architecture. The ball our juggler focuses on could progressively become a bad choice (for instance, because the wind or another ball collides with this one). In this case, like a real human, the juggler fails to catch the ball.
- The abilities to make approximative reasoning with a nonsymbolic and nonexplicit perception. Thanks to the use of NN, our juggler can adapt its arm's position in a precise position, and it can catch a ball even if some small disturbances arrive. Classical planning approaches are used to face these problems: if they use discrete variables, it implies the impossibility to adopt continuous values (such as the arm position); if they use approximative reasoning—which allows us to correct in line a drift from a planning—it implies that this drift should be provided and then explicitly represented.
- The abilities to adapt and to learn *online* the changing behavior of the environment. Our architecture can learn the environment. Of course, it is the case with classical reinforcement learning algorithms, but with this kind of algorithms, one learns qualities associated to discrete states. This mechanism takes a very long time and is not tractable in-line during an interaction with a human. Moreover, it generally addresses discrete decision when, for our juggler, the decision leads to a precise position of the hand. In our case, the system does not only recognize a changing of behavior but can also learn this change. From this point of view, our work is close to [47], which is able to teach to a robot continuous movements in-line.

In summary, without our architecture, the juggler would be unable to *credibly lose* its ball and to adapt to a human juggler, which never interacts exactly in the same way because it is the human nature for behavior to be imprecise but rarely irrelevant.

5.5. Limits

The drawbacks of all these important properties are as follows: (1) the lack of correlation with real data; and (2) the need for dedicated models of predictions.

First, let us discuss the *lack of correlation with real data*. It is obvious that the more an agent is autonomous, the less it is possible to control it. Because we need an autonomous agent, we must be happy about this autonomy. Nevertheless, to improve its credibility, it is necessary to refine some details about the behavior. We need to better fit the behavior with human dynamics. In other words, our agent is credible because it adapts its behavior to its perceptions, but even if the manner it performs this adaptation complies with cognitive considerations broadly, it is not the case for details comparing to the real reaction of a human. To overcome this problem, we need to improve the models from real cases and to add physical properties to the body of the agent. Some works address this issue [48]. One of our objective is to mix our proposition with this kind of works.

Concerning *the need for dedicated models of prediction*, even if our proposition is very generic, that is, anticipating from a virtual simulation of the agent behavior in a virtual world, we use NN for the example of juggler. The proposition of NN T1 and T2 is very specific to this case. For the moment, each new case of application of our framework will need studies of anticipative models adapted to the specific domain.

These drawbacks indicate how some work still remains to address a real autonomous agent.

6. CONCLUSION

For the behavioral believability of the interaction of a virtual entity to increase, it would seem essential to integrate an anticipatory capacity by which the behavior of other entities and their consequences on the environment can be predicted. To do so, we suggest an architecture by which the three modes—reactivity, predictability, and adaptability—can function asynchronously in parallel. The prediction is made by an autonomous world of a *simulation within a simulation*, in which the entity can simulate itself (with its own behavioral model) and its environment (with the representations that it constructs of the behaviors of other entities).

We developed a virtual juggler that anticipates the trajectory of the balls without calculating them precisely. Indeed, the juggler hypothesizes using an open and uncertain environment with variable properties, that is to say, that are unknown from an analytical standpoint. We therefore use universal approximators obtained through learning.

Two types of predictions offer answers to the questions of which will be the next ball to catch and where it will fall. Another prediction accounts for the balls thrown by a human user using a Wiimote. These predictions are made and refined by NN. Through our application, known as JABU, we were able to evaluate our proposal using a number of experiments.

Of course, this work does not address the quality of gestures, nor the comparison with real data from juggling. To do that, we have in perspective the improvement of this proposition with realistic models of gesture. For the moment, the purpose was to show that it is possible to exhibit plausible failures in the task when taking into account simulation and anticipation. Another important point is that the juggler is able to juggle with people who take part in an unpredictable environment.

We are currently orienting our work toward the addition of different juggling strategies. The imaginary world of a simulation within a simulation could be used to test many different possibilities. The results of such simulations would help to provide strategies that are better adapted to the virtual world.

We would also like to work on a new kind of prediction dealing with the behavior of the human interacting with the juggler. In the current application, the interaction between the human and the virtual juggler occurs using a Wiimote. This peripheral device measures the movements of the human user's hand. The virtual juggler has access to these data, thus enabling it to "watch" the user. A recognition mechanism could thus be conducted by the juggler using the observed data, to identify information that could offer clues about the human user's future behavior.

In this article, we did not evaluate yet our proposal in terms of its believability. It will be the more challenging perspective. As believability is subjective, evaluation is a critical and complex step. Even if it was not intended to, Turing's test is still considered as a reference for believability evaluation [49]. In its standard interpretation, a judge must interact with a human and a machine. If, after a certain amount of time, the judge cannot tell which one is artificial, the machine is said to be intelligent. Following this idea, parameters for believability evaluation methods were presented [50–52], but problems are not solved. First, the protocol could be debated. For instance, some studies propose to cast doubt on the nature of the presented character(s) to avoid bias induced by prejudices (human are presented as artificial). Second, the computation of the overall believability score is complex. For instance, in case of a multiple-question form, experimenters may have too much influence on the results. Next, it is also necessary to decide if judges are actors or only spectators. Although actors can actively test evaluated characters, spectators are more focused on them and can notice much more details in the behaviors. Finally, the choice of the judges is really important. Cultural origins [50] and level of experience [53] may have a noticeable impact on believability scores.

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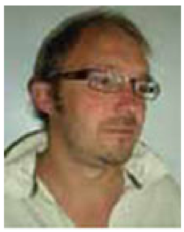
AUTHORS' BIOGRAPHIES

C. Buche (1979) is an associate professor at the National Engineering School of Brest, which belongs to the European University of Britain, a member of the IHSEV team of the LAB-STICC and a member of the European Center for Virtual Reality (CERV). His research concerns the simulation of adaptive behaviors. He is the leader of the JABU project.



P. De Loor (1968) is a professor at the National Engineer School of Brest. He is the leader of the IHSEV team of the LAB-STICC Labs. He is interested in the link between artificial intelligence, cognitive science and virtual reality.