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Simulation theory and anticipation for interactive virtual character in an uncertain world

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This paper deals with simulations of real-time to anticipate and simulate the world behavior.
interactive character behavior. The underlying For that purpose, we propose a conceptual
idea is to take into account principles from framework where the entity possesses an au-
cognitive science, in particular, the human ability tonomous world of simulation within simulation,

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8 in which it can simulate itself (with its own model of behavior) and the environment (with
9 an abstract representation, which can be learnt,
10 of the other entities behaviors). This principle
11 is illustrated by the development of an artificial
12 juggler, which predicts the motion of balls in the
13 air and uses its predictions to coordinate its own
14 behavior while juggling. Thanks to this model it
15 is possible to add a human user to launch balls
16 that the virtual juggler can catch whilst juggling.

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33 **Keywords:** anticipation, real-time interac-
34 tion, decision making, behavioral model, virtual
35 juggler, virtual character, computer animation

41 1 Introduction

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45 This study is focused on the real-time interaction
46 between a virtual character, or agent, and a dy-
47 namic open world. In this world, real users are
48 able to disturb, at any time, the behavior of the
49 virtual character. In this case, using a precise rep-
50 resentation of the behavior of the world is impos-

sible. However, it is a very important challenge
to develop such a kind of behavior in order to
address complex sensorimotor interactions with
humans for video games, virtual theater, sport or
any application implying improvisation, adapta-
tion or co-evolution between human and virtual
creatures. Despite the availability of numerous
propositions for interactive behavior in computer
animation (see section 2), our goal is to use ideas
and concepts from cognitive science to enhance
credibility about interactions. To be more pre-
cise, focus is on the simulation theory, the hu-
man's anticipation ability and capacity to learn
the world with which it is interacting. The re-
sult is that interactive characters can improve, in
real-time, their behavior adaptation ability. This
paper is organized as follows: an overview on in-
teractive animation of virtual characters, and on
main challenges in this field, is presented in sec-
tion 2. It points out that, usually, the dynamics
of the environment is pre-given and steady. Sec-
tion 3 gives three concepts from cognitive sci-

ences considered as important in human ability during interactions within an uncertain and variable environment. These concepts are anticipation, simulation and attention. Then, section 4 proposes a conceptual framework based on 3 parts: i) general knowledge about the environment which can be learnt during interactions, ii) simulation world, which allows the anticipation of the current interaction and the definition of the object of attention of the character and iii) control of the virtual agent in interaction with its own world, but based on the prediction issued from the simulation. An illustration of this model is provided in section 5 through implementation of an interactive juggling game. It shows the ability of the virtual juggler to adapt its reaction to various disturbances, to play with other virtual jugglers and also with a human player.

2 Interactive characters

Numerous investigations have been aimed at simulating the behavior of virtual characters in real-

time. Several approaches dealt with the development of algorithms dedicated to the synthesis of the gesture quality [1, 2]. But, none of them took into account interaction abilities of the character. At the opposite, some models developed in robotics are interaction oriented and rely on cognitive science, but the problem of animation realism is not addressed [3]. In-between hybrids architectures can describe high level real-time reasoning, thanks to state machines, planning algorithms and synchronization mechanisms [4, 5]. Some other ones are rule-based [6], but, generally, the management of interactions introduces a bottleneck in term of the capabilities to take into account all possibles scenarios. In the domain of animated and conversational agent, interaction is more generally addressed. For instance, JACK is an architecture able to manage the dialog between two agents [7], REA [8] allows the inclusion of the user's gaze and provides algorithms to link voice to gestures. GRETA [9] communicates with complex emotions and MAX

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8 [10] recognizes the hand gestures thanks to the
9 treatment of data issued from a motion capture
10 glove. [11] identify some subtle interactively
11 contingent phenomenas during human interac-
12 tion which lead to a *social resonance*. For in-
13 stance, [12] presents a system for authoring inter-
14 active characters. ELCKERLYC [13] is an adap-
15 tation of SAIBA which is able to anticipate the
16 behavior of a user to change the animation from a
17 set of precomputed possibilities. Because it relies
18 on anticipation, it is close to our work but limited
19 by the use a predefined animations. Finally, close
20 to our applicative example, [14] propose an archi-
21 tecture for the hand coordination of a virtual jug-
22 gler. However, as these authors focused on im-
23 portant technical issues, some essential features
24 of human interaction, addressed in cognitive sci-
25 ence, were neither considered, nor made explicit
26 by these numerous approaches. These features
27 would be able, in the long run, to enhance cred-
28 ibility of the dynamics of interactive behaviors.
29 In a first step, they can improve the adaptabil-

ity of a virtual character to different types of dis-
turbances issued from a poorly known world be-
cause of it's variability and its opening on hu-
mans.

3 Three notions from cognitive sciences

Cognitive science is a wide domain, enriched by many points of view. Here, focus is only on the three key concepts addressed in this study.

1. *Anticipation*: animals and humans use their memories of the past so as to anticipate the consequences of their actions and the behavior of those around them. Some philosophers put the anticipation at the basis of cognition [15, 16]. The phenomena of anticipation are held parallel to the reasoning and they allow active correction of the action [17].
2. *Simulation*: this concept is close to anticipation, but it explains how anticipation is per-

formed. Some psychologists and neuroscientists claim that the brain is a simulator for action in the environment [18, 19, 17, 20]. With simulation theories, anticipation is not a disembodied abstract and rational reasoning, but rather an active process based on the imagination of interaction with an imaginary world: it is an explicit internal simulation.

3. *Attention*: sensory anticipation includes the use of predictive environmental models to orient the entities' perceptions more effectively, especially in order to process expected event rather than to take into account the whole environment [18, 21]

4 Conceptual Framework

Our models are part of a conceptual framework described in Figure 1. It takes into account notions like anticipation and explicit internal simulation. To take a decision and to control its inter-

action into a *virtual world* (at the bottom of the Figure), an autonomous agent uses predictions provided by a simulation (the *imaginary world* in the middle of Figure 1), performed from approximate knowledge, *i.e.* this simulation is not the result of an analytic calculus from accurate physical features of the environment. These features are approximated in an *abstract world* (at the top of the Figure) and hence, some variations in the future of the *virtual world* are possible. Hence, the agent needs to perpetually correct its control through comparison of approximated anticipations against real perceptions (when they exist). The result is a possibility of error of estimation and then of failure during an interaction. Moreover, these failures are not arbitrary because they realize a natural feature: an approximation during anticipation. For instance, the more surprising a disturbance is, the less efficient the behavior is. In addition, section 5 shows that these approximations can be used to perform active perception by the virtual juggler, and thus reflect the concept

of attention (see section 3).

Finally, the *abstract world* is a sum of approximative knowledges about the dynamical features of the world. These knowledges are learnt during interactions. Thus, the agent can adapt its worldview through experience. For that, different techniques from machine learning can be used (reinforcement, lazy learning, etc). This idea was used to define the behavior of virtual sheepdogs able to anticipate and to learn the decision making of virtual sheeps by the use of fuzzy cognitive maps [22]. Now, we will show that the conceptual framework presented here can be applied in a sensorimotor interaction context with humans.

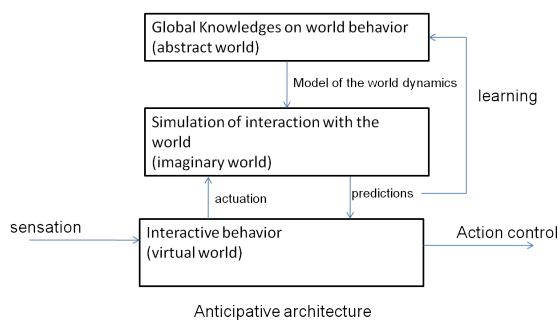


Figure 1: Conceptual framework for anticipative agents.

5 Example : interactive

Juggler

The problem of virtual juggler was discussed in [23, 14]. But, in these approaches, neither the modeling of approximative anticipation nor the theory of simulation was taken into account. More generally, the relationships between cognitive sciences and character's behavior were not addressed. Here, we will show that the proposed conceptual framework can account for not only adaptation, but also plausible errors, through more or less predictable interactions, especially, with a real human character. An illustration of its application is presented in Figure 2. This application is called JABU: Juggler with Anticipatory Behavior in virtual Universe (see Figure 3).

The virtual world of the juggler has physical properties (inertia, gravity, wind, etc.) through the use of the ODE¹ physics engine. Of course, these quantities are not explicit in the model of

¹Open Dynamic Engine, <http://www.ode.org/>

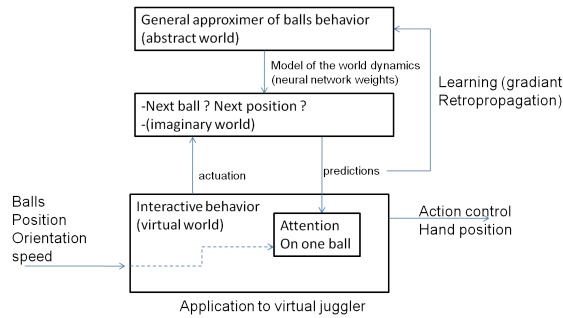


Figure 2: Instantiation of the framework for a virtual juggler.



Figure 3: The JABU application.

control. This control is adjusted through an attentional process focused on the *next* (anticipated) ball (actually one ball by hand). The approximate position of the balls is made by their simulation in the imaginary world of juggling. The function approximation properties of this imaginary world come from different neural networks.

The abstract world corresponds to the weights of the arcs of these networks. Since they are universal approximators, we will see later that they allow real-time adaptation of the juggler gestures to different types of disturbances (this is also illustrated by the video associated with this article). The implementation of these principles is described hereafter.

5.1 Decision-making process

The hands have independent functions: this means that there are neither complex juggling moves nor tricks, but simply a succession of ball catches and throws, where each movement is independent of the others. As soon as a ball comes

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7 at the same height as the hands, it must be caught Then, this reception point can be refined. In or-
8 and thrown back. Hence, at this stage, the goal is der to do so, the hand must estimate and correct
9 not to get a realistic dynamics of gesture; no com- the anticipated trajectory of the target ball (pre-
10 plex arm control model is used. Nevertheless, the diction T2) which is the *object of attention*. Each
11 time taken for a hand to move is not negligible hand will therefore be able to catch or miss the
12 and makes the juggler at risk of delayed move, target ball. If the ball is caught, the juggler will
13 which means missing the ball; this is also ampli- be able to throw it in the air. Whatever the future
14 fied by prediction errors. As mentioned above, of the first ball (caught or missed), the juggler's
15 the precise reproduction of the movement is not hand once again starts looking for the next flying
16 our priority and the hand's movement time is an ball.

17 empirically adjustable variable which reflects the
18 delay between the decision being made and the
19 action being carried out. In the following section,
20 to facilitate the readability while keeping things
21 brief, any reference to some hand activity means
22 that the theoretical model was implemented for
23 the anticipatory decision-making applied to our
24 juggler.

25 The different phases of juggling are as follows.
26 The juggler begins by looking for a ball in the air.
27 Once the ball has been spotted, the hand has to be
28 at an estimated reception point (prediction T1).

5.2 Predictions

29 Within the context of juggling, information must
30 be gathered quickly in order to maintain the jug-
31 gling dynamics. The use of perceptron-type neu-
32 ral networks (NNs) to make predictions about the
33 trajectory is adequate. Indeed, NNs are quickly
34 executed, and online learning occurs both quickly
35 and effectively. Furthermore, NNs correspond to
36 the need to manipulate (both spatial and tempo-
37 ral) digital data. It is, of course, also possible to
38 use deterministic 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 [17].

5.2.1 Prioritizing the balls (T1)

NN T1 provides the estimated temporal and spatial data for each ball at the moment it is thrown (see Figure 4). These data are used to categorize the balls and attribute them priorities so as to trigger 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 has to be caught (see Table 1).

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

Table 1: Inputs/Outputs of NN T1. V_x, V_y, V_z

are the ball speeds along the three spatial axes, Δt is the time at which the ball is supposed to reach the point Δx and Δy at the height of the hand.

5.2.2 Refining the prediction of the target ball (T2)

NN T2 refines the spatial prediction about the place where a ball will fall while it is falling down

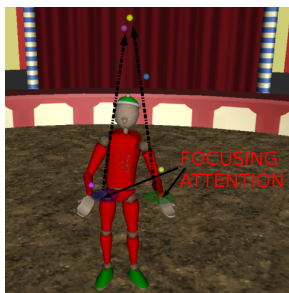


Figure 4: T1 estimates the position at which it will cross the hand plane (represented with circles) and how long it will take.



Figure 5: At any given time as the ball falls, T2 makes a more accurate estimation of its position in Δt seconds (represented by blurred ball).

(see Figure 5 and Table 2). Information can be obtained at different temporal levels (according to Δt).

5.3 Interaction between virtual jugglers and with the human

The general features of this proposition allow interactions between several jugglers. To do that, the only change is the direction of the ball launched by each juggler (see Figure 6).

Inputs	Outputs	Parameter	Objectives
V_x	Δx	Δt	Refined spatial predictions
V_y	Δy		
V_z	Δz		

Table 2: Inputs/Outputs of NN T2.



Figure 6: Multiple-jugglers.

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8 The juggler can also catch a new ball thrown
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10 by a human user (Figure 7). This is useful for
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12 evaluating the believability of the virtual jug-
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14 gler (real-time decision-making, online adapta-
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16 tion, etc.). Introducing a human user also re-
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18 quires the introduction of a new type of predic-
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20 tion (T3). One should note that T3 is similar
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22 to the prediction T1, except that the ball is not
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24 thrown by the virtual juggler. The human user
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26 interacts with the virtual juggler by using a Wi-
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28 imote (remote game controller from the Nintendo
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30 Wii console). This peripheral device measures
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32 the movements of the human user's hand.
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53 Figure 7: A human can juggle with virtual jug-
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55 glers using the Wiimote.
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5.4 Learning

The abstract world is represented by the functions encoded in the NN T1, T2 and T3. They are updated in line from the observation of several variables. In its example base, NN T1 has access to throws made by the juggler itself (low speed along x and y axes) whereas NN T3 records the balls thrown at a distance by a third person (much greater speeds). Each hidden layer has 19 neurons, which leads to $3 \times 19 \times 19 \times 3$ multilayer perceptrons. Learning is, thus, conducted with a maximum of 100 iterations using the FANN². The parameters to be determined for the NN of T1 and the NN of T2 are h and Δt , respectively. In the example under study, $h = 2.5cm$ and $\Delta t = 0.1s$.

²Fast Artificial Neural Network (FANN) library available at <http://leenissen.dk/fann/>

5.5 Disturbing the environment

online

This section will deal with the evaluation of the anticipatory mechanism with its qualities and impact on decision-making and the final result: the juggler animation. The generalization abilities of NN allow the in line adaptation of the juggler's motion to disturbances. For the tests, the initial conditions are varied over a given time. Moreover, 42 balls are thrown towards the virtual juggler (one ball every 0.75 seconds). The purpose is to observe the number of balls missed by the juggler (*i.e.* which fall below its knees and which it is unable to catch). Two other experiments consist in disturbing the juggler to validate its robustness to variability in the environment. At first, jerks are introduced in the projectile trajectories because they become maces rather than balls (see Figure 8). In this case-study, through the prediction by NN T1 is less accurate, NN T2 is able to correct it properly, and the juggler continues to juggle when balls are *transformed* in maces.

Second, gravity in the virtual environment is varied, and wind is added (see Figure 9). The juggler is not informed of these changes.



Figure 8: Juggling with maces.

Figure 10 shows the result for gravity variations. In abscissa, the different values of gravity in m/s^2 . In ordinate, the number of balls which are dropped is an average over 10 tests of one minute each for each gravity value. One can observe that juggling is possible for gravitational values between 6 and 15 (normal gravity: 9.81). In cases of extremely low gravity, few balls are recorded as dropped, as they have not time to fall to the ground during the short simulation time. Figure 11 shows results for wind variations. The acceleration according to wind speed (in m/s^2 ,

with direction indicated by positivity or negativity) is in abscissa. The number of dropped balls is in ordinate. The average values are taken for 5 simulations for each wind value. About juggling, the range of speeds in which the juggler continues to juggle correctly is much smaller (between $-0.2m/s^2$ and $+0.2m/s^2$).



Figure 9: Disturbing the environment conditions in line (wind, gravity).

6 Conclusion

This study was based on the assumption that the behavioral believability of a virtual entity can be increased by integrating an anticipatory ability enabling the prediction of the behavior by other entities and their impact upon the environment.

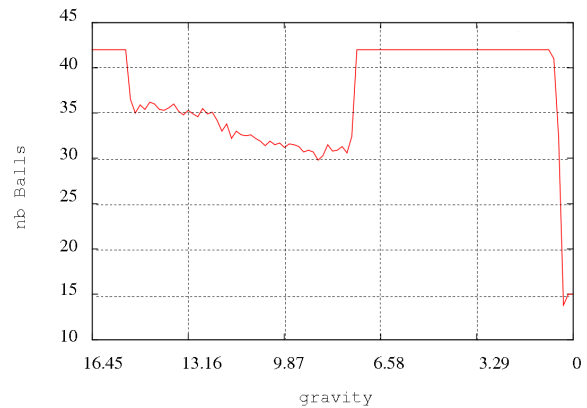


Figure 10: Average number of dropped balls according to gravity.

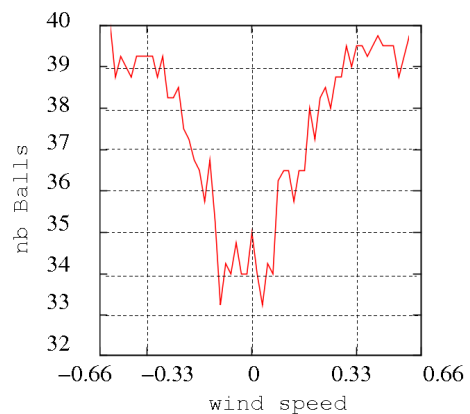


Figure 11: Average number of dropped balls according to wind.

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8 This led us to develop a conceptual framework the set of symbols which can represent the behav-
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10 taking into account some results from cognitive ior in the imaginary world.
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12 science. Its relevance was tested on the case-
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14 study of juggling: a virtual juggler anticipates the
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16 trajectory of balls without calculating them ac-
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18 curately. Indeed the juggler hypothesizes within
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20 an open and uncertain environment with variable
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22 properties, that is to say, that are unknown from
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24 an analytical standpoint. Universal approxima-
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26 tors obtained through learning are used. One
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28 problem is that this type of approximator is well
29
30 adapted to trajectories prediction but is certainly
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32 worst to address more complex behavior like the
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34 anticipation of human activity for instance. In
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36 such a case, it is important to address other pre-
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38 dictive model without losing the general features
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40 of our proposition. For example, in [22], we pro-
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42 pose an algorithm to learn a fuzzy cognitive map.
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44 Such kind of models are able to take into account
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46 behavior including decision choice and memory.
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48 Of course, using such model implies to define the
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50 link between the perception of the character and
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Of course, this study address neither the qual-
ity of gestures, nor the comparison with real data
from juggling. To do that, we have in perspective
the improvement of this proposition with realis-
tic models of gesture by integrating works like
[24]. 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.

We are currently orienting our investigations
towards the addition of different juggling strate-
gies. The imaginary world of a simulation within
a simulation could be used to test many differ-
ent possibilities. The results of such simulations
would help to provide strategies which are bet-
ter adapted to the virtual world. In addition, we
would also like to work on a new kind of pre-
diction dealing with the behavior of the human
interacting with the juggler.

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