

# A Motivational Model of Action Selection for Virtual Humans

Etienne de Sevin<sup>\*</sup> and Daniel Thalmann<sup>†</sup>  
EPFL Virtual Reality Lab - VRlab  
CH-1015 – Lausanne – Switzerland

## ABSTRACT

Nowadays virtual humans such as non-player characters in computer games need to have a real autonomy in order to live their own life in persistent virtual worlds. When designing autonomous virtual humans, the action selection problem needs to be considered, as it is responsible for decision making at each moment in time. Action selection architectures for autonomous virtual humans should be individual, motivational, reactive and proactive to obtain a high degree of autonomy. This paper describes in detail our motivational model of action selection for autonomous virtual humans in which overlapping hierarchical classifier systems, working in parallel to generate coherent behavioral plans, are associated with the functionalities of a free flow hierarchy to give reactivity to the hierarchical system. Finally, results of our model in a complex simulated environment, with conflicting motivations, demonstrate that the model is sufficiently robust and flexible for designing motivational autonomous virtual humans in real-time.

**CR Categories and Subject Descriptors:** I.3.7 [Three-Dimensional Graphics and Realism]: Animation; I.2.0 [General]: Cognitive simulation; J.7 [Computers in others systems]: real-time

**Additional Keywords:** action selection, motivations, autonomy, reactivity, proactiveness, attention, virtual humans.

## 1 INTRODUCTION

Autonomous virtual humans have a wide range of applications with the new developments of multi-player and interactive entertainments such as games, learning and training applications or film animations [1]. Although graphics technology allows the creation of environments looking incredibly realistic, the behavior of computer controlled characters (referred to as non-player characters) often leads to a shallow and unfulfilling game experiences [2]. For example in role-player games, the non-player characters inhabiting persistent virtual worlds should give the illusion of living their own lives to be more realistic, instead of staying static or having limited or scripted behaviors. The key goal is to devise an agent architecture which can be used to create more autonomous and believable virtual humans. Most of virtual human architectures are efficient but have a contextual autonomy in the sense that they are designed to solve specific complex tasks (cognitive architectures), follow scripted scenarios (virtual storytelling) or interact with other agents (BDI architectures). However autonomous virtual humans need to continue to take decisions according to their internal and external factors in order to live their own lives after complex tasks, scripted scenarios or social interactions are finished.

<sup>\*</sup> etienne.desevin@epfl.ch

<sup>†</sup> Daniel.thalmann@epfl.ch

The principal problem when you design autonomous virtual humans is that they have to take their own decisions in real-time in a coherent and effective way. Therefore the action selection problem needs to be considered, as how to choose the appropriate actions at each point in time so as to work towards the satisfaction of the current goal (its most urgent need), paying attention at the same time to the demands and opportunities coming from the environment, and without neglecting, in the long term, the satisfaction of other active needs [3]. It corresponds to the executive part of the agent intelligence and what players should do in the game *The Sims* [4].

Although motivations are a prerequisite for any cognitive systems and are very relevant to emotions [5], the internal context coming from motivations is often missing in computational agent based systems [6]. “Autonomous” entities in the strong sense are goal-governed and self-motivated [7]. The self-generation of goals by the internal motivations is critical in achieving autonomy [8]. Motivations should be defined for each virtual human in order to give them individualities before focusing on emotions, cognition or social interactions. Motivational autonomous virtual humans give the illusion of living their own life increasing the believability of persistent virtual environments. Therefore action selection mechanisms for autonomous virtual humans should be individual and motivational in order to achieve a real autonomy. Moreover it is better to embed complexity within a single agent than within communication process for two reasons: because communication is unreliable and because existing AI and software engineering can reduce the complexity of within-agent coordination [9].

Besides being motivational and individual, action selection architectures for autonomous virtual humans should be reactive as well as proactive [10] to be efficient in real-time. Most of behavior planners don’t manage interruptions such as opportunist behaviors. Based on theories from ethology, artificial life researchers [11, 12] have proposed a set of design criteria that action selection mechanisms should respect to be effective: priority of behaviors, persistence or hysteresis, compromised actions, opportunism and quick response time. The model should be reactive to adapt rapidly to the external factors and should also plan consistent goal-oriented behaviors so that the virtual humans could satisfy their motivations. The transitions between reactions and planning should be rapid and continuous in order to have coherent and appropriate behaviors in changed or unexpected situations.

In this paper, we present a motivational action selection architecture for individual autonomous virtual humans. Decisions are taken in real-time to satisfy conflicting motivations according to the environmental perceptions. After summarizing previous work useful for designing reactive and goal-oriented action selection mechanisms, we describe in detail our model. A complex simulated environment is created, and the model is tested, with conflicting motivations, in our real-time development framework, VHD++ [13]. Finally, results show that our model is sufficiently robust and flexible enough for modeling motivational autonomous virtual humans in real-time.

## 2 RELATED WORK

Postulated since the early ethologists and observed in research in natural intelligence, hierarchical and fixed sequential orderings of actions into plans are necessary to attain the specific goals and to obtain proactive and intelligent behaviors for complex autonomous agents [14]. They reduce the combinatorial complexity of action selection, i.e. the number of options that need to be evaluated in selecting the next act. Hierarchical systems are often criticized because of their rigid, predefined and unreactive behaviors [11, 15]. To obtain more reactive systems, constant parallel processing had to be added [16, 17]. However fully reactive architectures increase the complexity of action selection despite the use of hierarchies. To take advantage of both reactive and hierarchical systems, some authors had implemented an attention mechanism. It reduces the information to monitor and then simplifies the task of action selection [18, 14]. These architectures with selective attention can surpass the performance of fully reactive systems, despite the loss of information and compromise behaviors satisfying several motivations at the same time [14]. In our approach [19], we choose to associate reactive and goal-oriented hierarchical classifier systems [20] associated with the functionalities of a free flow hierarchy [16] for the propagation of the activity to give reactivity and flexibility to the hierarchical system. It permits to have no loss of information and compromise behaviors necessary for effective action selection mechanisms. Moreover we define a selective attention system to assist the architecture with choosing the next behavior.

### 2.1 Hierarchical classifier systems

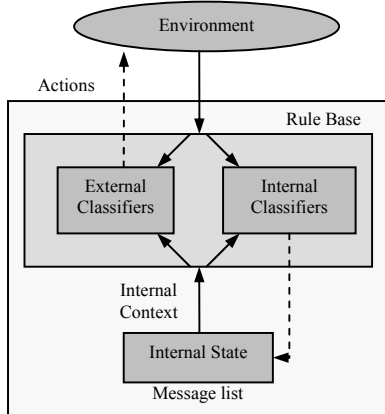


Figure 1. General description of a hierarchical classifier system.

Hierarchical classifier systems [20] provide a good solution for modeling complex systems by reducing the search domain of the problem using weighted rules. A classical classifier systems has been modified in order to obtain a hierarchical organization of the rules, instead of a sequential one. A hierarchical classifier system can generate reactive as well as goal-oriented behaviors because two types of rules exist in the rule base: externals, to send actions directly to the motors, and internals, to modify the internal state of the classifier system. The message list contains only internal messages, creating the internal state of the system, which provides an internal context for the activation of the rules. The number of matching rules is therefore reduced, as only two conditions need to be fulfilled to activate rules in the base: the environmental information and the internal context of the system. Internal messages can be stacked in the message list until they have been carried out by specific actions. Then behavioral sequences of actions can easily be performed. For example, the virtual human

can move to a specific location from anywhere with the aim of preparing the virtual human to perform motivated actions that will satisfy his motivations. Table 1 shows how a hierarchical classifier system can generate such a sequence of actions to satisfy hunger.

### 2.2 Free flow hierarchy

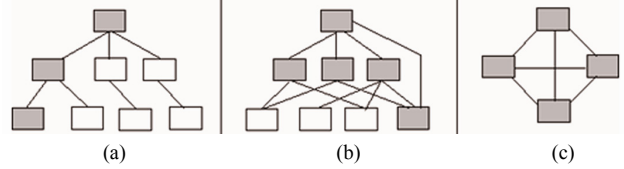


Figure 2. (a) corresponds to hierarchical decision structure where the choice is made at each level. (b) is a free flow hierarchy, the choice is made only at the lowest level. (c) is a neural network without hierarchy.

Tyrrell [16] tested performances (genetic fitness) of many action selection mechanisms in complex simulated environments with many motivations. He concluded that the most appropriate action selection mechanism for managing many motivations in complex simulated environments is the free flow hierarchy. The key idea is that, during the propagation of the activity in the hierarchy, no decisions are made before the lowest level in the hierarchy (action level) is reached, violating the subsumption philosophy. Summations of activities are then possible and in the end the most activated node is chosen. Free flow hierarchies increase the reactivity and the flexibility of the hierarchical systems because of unrestricted flow of information, combination of preferences and the possibility of compromise and opportunist candidates. All these functionalities are necessary to select the most appropriate action at each moment in time.

## 3 THE MOTIVATIONAL MODEL OF ACTION SELECTION

Our motivational model of action selection has to choose the appropriate behavior at each point in time according to the motivations and environmental information. It is based on overlapping hierarchical classifier systems (HCS) working in parallel to generate behavioral plans. It is associated with the functionalities of a free flow hierarchy for the propagation of the activity to give reactivity and flexibility to the hierarchical system.

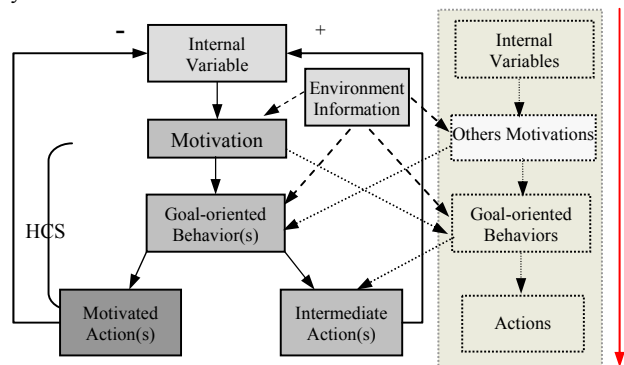


Figure 3. A hierarchical decision loop of the model for one motivation (→ activity at each iteration).

In the model, hierarchical decision loops, one per motivation, are running in parallel. For clarity purposes, Figure 3 depicts a hierarchical decision loop for one motivation. It contains four levels:

1) **Internal variable** represents the homeostatic internal state of the virtual human and evolves according to the effects of actions. The action selection mechanism should maintain them within the comfort zone (§ 3.2).

2) **Motivation** is an abstraction corresponding to tendency to behave in particular ways according to environmental information (§ 3.1), a “subjective evaluation” of the internal variables (§ 3.2) and a hysteresis (§ 3.3). Motivations set goals for the virtual human in order to satisfy internal variables.

3) **Goal-oriented behaviors** represent the internal context of the hierarchical classifier system (§ 3.4). They are used to plan sequences of actions such as reaching specific goals. In the end, the virtual human can perform motivated actions satisfying motivations.

4) **Actions** are separated into two types. *Intermediate actions* are used to prepare the virtual human to perform *motivated actions* that can satisfy one or several motivations (§ 3.5). Intermediate actions often correspond with moving the virtual human to specific goals in order to perform motivated actions. Both have a retro-action on internal variable(s) (§ 3.6). Intermediate actions increase them, whereas motivated actions decrease them.

The motivational model of action selection is composed of overlapping hierarchical decision loops running in parallel. The number of motivations is not limited. Hierarchical classifier systems contain the three following levels: motivations, goal-oriented behavior and actions. The activity is propagated throughout the hierarchical classifier systems according to the two rule conditions: internal context and environment perceptions. Selection of the most activated node is not carried out at each layer, as in a classical hierarchy, but only at the end in the action layer, as in a free flow hierarchy. In the end, the action chosen is the most activated.

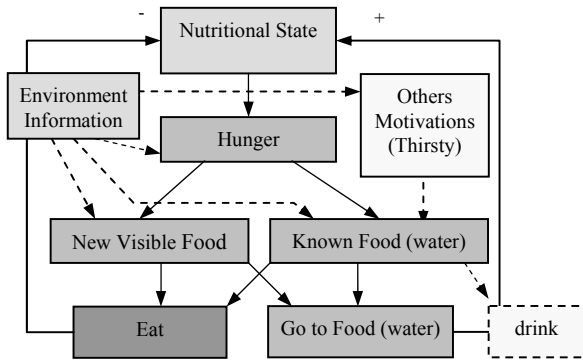


Figure 4. hierarchical decision loop example: “hunger”

An example of the hierarchical decision loop for the motivation “hunger” depicted in figure 4 helps to understand how the motivational model of action selection for one motivation works.

### 3.1 Environmental information

To satisfy his motivations autonomously, the virtual human should be situated in his environment, i.e. he can sense his environment through his sensors and acts upon it using his actuators [21]. Therefore the virtual human has a limited perception system which can perceive his environment around him. He can then navigate in the environment, avoiding obstacles with the help of a path-planning, and move to specific goals to satisfy motivations by interacting with objects. Environment perceptions are integrated at two levels in the model: motivations and goal-oriented behaviors, to be more reactive. Indeed two types of opportunist behaviors, which are the consequences of the reactivity and the flexibility of the model, are possible. First,

when the virtual human passes near a specific place where a motivation can be satisfied, the value of this motivation (and the respective goal-oriented behaviors) is increased proportionally to the distance to this location. For example, when a man passes near a cake and sees it, even if he is not really hungry, his level of hunger increases. Second, when the virtual human sees on his way a new, closer location where he can satisfy his current motivation, the most appropriate behavior is to interrupt dynamically his current behavior to reach this new location, instead of going to the original one.

### 3.2 “Subjective evaluation” of motivations

Instead of designing a winner-take-all hierarchy with the focus of attention [14, 17], we develop a “subjective evaluation” of motivations corresponding to a non-linear model of motivation evolution. It allows having a selective attention with the advantages of free-flow hierarchies: unrestricted flow of information, possibilities of compromise and opportunist candidates. A threshold system (figure 5), specific to each motivation and inspired by the viability zone concept [22], reduces or enhances the motivation values to maintain the homeostasis of the internal variables. One of the main roles of the action selection mechanism is to preserve the internal variables within their comfort zone by choosing the most appropriate actions. This threshold system can be assimilated with degrees of attention. It limits and selects information to reduce the complexity of the decision making task [14]. In other models, emotions could play this role [23]. It helps to solve the choice among multiple and conflicting goals at any moment in time and reduces the chances of dithering or pursuing a single goal to the detriment of all others.

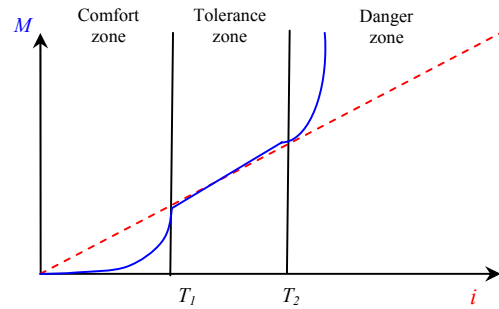


Figure 5. “Subjective” evaluation of one motivation from the values of the internal variable.

We define the subjective evaluation of motivation as follow:

$$\begin{cases} M = T_1 e^{(i-T_1)^2} & \text{if } i < T_1 \\ M = i & \text{if } T_1 \leq i \leq T_2 \\ M = \frac{i}{(1-i)^2} & \text{if } i > T_2 \end{cases} \quad (1)$$

where  $M$  is the motivation value,  $T_1$  the first threshold and  $i$  the internal variable

If the internal variable  $i$  lies beneath the threshold  $T_1$  (comfort zone), the virtual human does not pay attention to the motivation. If  $i$  is between both thresholds (tolerance zone), the value of the motivation  $M$  equals the value of the internal variable. Finally, if  $i$  is beyond the second threshold  $T_2$  (danger zone), the value of the motivation is amplified in comparison with the internal variable. In this case, the corresponding action has more chances to be chosen by the action selection mechanism, to decrease the internal variable.

### 3.3 Hysteresis and persistence of actions

The difficulty to control the temporal aspects of behaviors so as to arrive at the right balance between too little persistence, resulting in dithering among activities, and too much persistence so that opportunities are missed or that the agent mindlessly pursues a given goal to the detriment of other goals [17]. Instead of using an inhibition and fatigue algorithm because of the difficulty to define inhibitions between motivations (for example watering and eating), a hysteresis has been implemented, specific to each motivation, to keep at each step a portion of the motivation from the previous iteration. In addition to the “subjective evaluation” of the motivation, it allows the persistence of motivated actions and the control of temporal aspect of behaviors:

$$M_t = (1 - \alpha) \cdot M_{t-1} + \alpha(M + e_t) \quad (2)$$

Where  $M_t$  is the motivation value at the current time,  $M$  the “subjective” evaluation of the motivation,  $e_t$  the environment variable and  $\alpha$  the hysteresis value with  $0 \leq \alpha \leq 1$

The goal is to maintain the activity of the motivations and the corresponding motivated actions for a while, even though the value of the internal variable decreases. Indeed, the chosen action must remain the most activated until the internal variables have returned within their comfort zone. A man goes on eating even if the initial feeling of hunger has disappeared, and stops only when he has eaten his fill. This way, the hysteresis limits the risk of action selection oscillations between motivations and allows the persistence of motivated actions. Otherwise, the virtual human would dither between several motivations, and in the end, none of them would be satisfied.

### 3.4 Behavioral sequences of actions

To satisfy motivations of the virtual human by performing motivated actions, behavioral sequences of intermediate actions need to be generated, according to environmental information and internal context of the hierarchical classifier system [20].

Table 1. Example for generating a sequence of actions using a hierarchical classifier system (timeline view).

Time steps	$t_0$	$t_1$	$t_2$	$t_3$	$t_4$	$t_5$	$t_6$
Environmental information	known food location, but remote			Near food	Food near mouth	No food	
Internal context (Message List)	hunger						
				reach food location			
Actions				Go to food	Take food	Eat	
Activated rules		$R_0$	$R_1$	$R_2$	$R_3$	$R_4$	

In the example (table1 and figure 6), hunger is the highest motivation and must remain so until the nutritional state is returned within the comfort zone. The behavioral sequence of actions for eating needs two internal classifiers ( $R_0$  and  $R_1$ ) and three external classifiers ( $R_2$ ,  $R_3$  and  $R_4$ ):

- $R_0$ : if known food location and the nutritional state is high, then hunger.
- $R_1$ : if known food is remote and hunger, then reach food location.
- $R_2$ : if reach food location and known food is remote, then go to food.
- $R_3$ : if near food and reach food location, then take food.
- $R_4$ : if food near mouth and hunger, then eat.

Here, the virtual human should do a specific and coherent sequence of intermediate actions in order to eat and then satisfy his hunger. In this case, two internal messages “hunger” and “reach food location” are added to the message list, thanks to the internal classifiers  $R_0$ , then  $R_1$ . They represent the internal state for the rules and remain until they are realized. To reach the known food location, two external classifiers,  $R_2$  and  $R_3$ , activate intermediate actions as many times as necessary. When the virtual human is near the food, the internal message “reach food location” is deleted from the message list and the last external classifier  $R_4$  activates the motivated action “eat”, decreasing the nutritional state. Furthermore, motivated actions weigh twice as much as intermediate actions because they can satisfy motivations. They therefore have more chances to be chosen by the action selection mechanism decreasing the internal variables until they’re back within the comfort zone. Thereafter the internal message “hunger” is deleted from the message list, the food has been eaten and the nutritional state is returned within the comfort zone for a while.

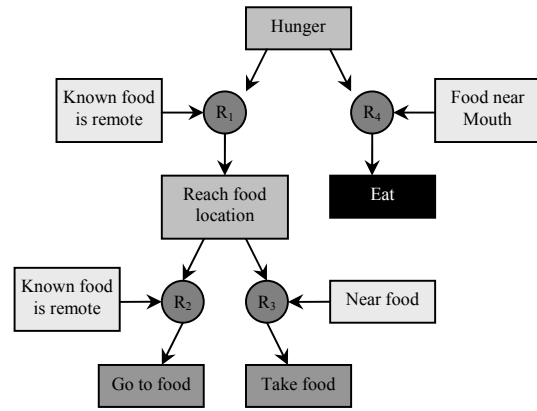


Figure 6. Example for generating a sequence of actions using a hierarchical classifier system (hierarchical view)

### 3.5 Compromise behaviors

In our model, the activity coming from the motivations is propagated throughout the hierarchical classifier systems, according to the free flow hierarchy [12]. A greater flexibility in the behavior, such as compromise behaviors where several motivations can be satisfied at the same time, is then possible. The latter have also more chances of being chosen by the action selection mechanism, since they can group activities coming from several motivations calculated as follow:

$$A_c = A_h + \frac{\sum_m^1 \beta A_i}{\sum_n^1 M_i} \cdot A_h \quad \text{if } A_m \geq S_c \quad (3)$$

where  $A_c$  is the compromise action activity,  $A_h$  the highest activity of compromise behaviors,  $\beta$  the compromise factor,  $A_i$  the compromise behaviors activities,  $m$  the number of compromise behaviors,  $M_i$  the motivations,  $n$  the number of motivations,  $A_m$  the lowest activity of compromise behaviors and  $S_c$  the activation threshold specific to each compromise action.

Compromise actions are activated only if the lowest activity of the compromise behaviors is over a threshold defined within the rule of the compromise action. The value of the compromise action should always base on the highest compromise behavior activity even if it is not the same one until the end. The corresponding internal variable should return in the comfort zone. However the other concerning internal variables by the effect of the compromise action, stop to decrease from an inhibition

threshold to keep the internal variables standardized. For example, let's say the highest motivation of a virtual human is hunger. If he is also thirsty and knows a location where there are both food and water, even if it is more remote, he should go there. Indeed, this would allow him to satisfy both motivations at the same time, and both corresponding internal variables to return within their comfort zone.

### 3.6 The choice of actions

As activity is propagated throughout the hierarchy, and the choice is only made at the level of the actions, the most activated action is always the most appropriate action at each iteration. This depends on the "subjective evaluation" of the motivations, the hysteresis, environmental information, the internal context of the hierarchical classifier system, the weight of the classifiers and the others motivations activities. Most of the time, the action receiving activity coming from the highest internal variable is the most activated action, and is then chosen by the action selection mechanism. As normally the corresponding motivation stay the highest until the current internal variable decreases in the comfort zone. Behavioral sequences of actions can then be generated by choosing intermediate actions at each iteration. Finally, the motivated action required to decrease the internal variables can be performed (see figure 10). However there are exceptions, such as when another motivation becomes more urgent to satisfy, or when opportunist behaviors occurs. In these cases, the current behavior is interrupted and a new behavioral sequence of intermediate actions is generated in order that the virtual human can satisfy this new motivation.

## 4 TEST SIMULATION IN VHD++

Still, a simulated environment is needed to test the functionalities of the motivational model of action selection. A 3D apartment was designed, in which the virtual human can "live" autonomously by perceiving his environment and satisfying different motivations at specific goals.

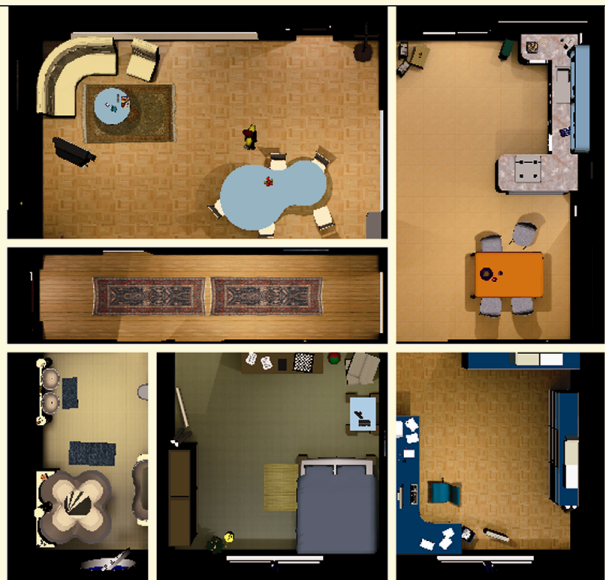


Figure 7. The simulated environment (apartment) in the 3D viewer.

We arbitrarily define twelve conflicting motivations that a human can have in this environment with their specific goals and the associated motivated actions, described in the table 2. You can define motivations corresponding to your application context.

Table 2. All defined motivations with associated actions and their goals.

motivations	goals		actions	
	goal	id	action	id
hunger	table	1	eat	1
	sink	2	eat1	2
thirst	sink		drink	3
	table		drink1	4
toilet	toilet	3	satisfy	5
resting	Sofa	4	sit	6
	bedroom	5	rest	7
sleeping	bedroom		sleep	8
washing	bathroom	6	wash	9
cooking	oven	7	cook	10
	sink		cook1	11
cleaning	worktop	8	clean	12
	shelf	9	clean1	13
	bathroom		clean2	14
reading	bookshelf	10	read	15
	computer	11	read1	16
communicating	computer		communicate	17
exercise	room	12	do push-up	18
	hall	13	do push-up1	19
	desk	14	do push-up2	20
	kitchen	15	do push-up3	21
watering	plant	16	water	22
compromises	table		eat and drink	23
	sink		eat, drink and cook	24
	computer		read and communicate	25
	bedroom		sleep and rest	26
	bathroom		wash and clean	27
default	sofa		watch TV	28
...	...		...	

At any time, the virtual human has to choose the most appropriate action between conflicting ones according to his motivations and environmental information. Actions can be done at specific goals in the apartment. Compromise behaviors are possible, for example the virtual human can drink and eat at the table. He can also perform different actions in the same place but not at the same time such as sleep or rest in the bedroom. The virtual human can finally perform the same action in different places: for example do push-up in the room or in the desk. The default action is watching television in the living room. Moreover he has a perception system to allow opportunist behaviors. The distance and its importance in the decision-making can be defined at the beginning and during the simulation.

Technically, the test of our motivational model of action selection for a individual virtual human [24] is done by implementing the model in VHD++ [13], a real-time framework for advanced virtual human simulations (see figure 15 in the color plate). An interface has been designed for monitoring, and changing if it is necessary, the evolution of the virtual human's internal variables, motivations and actions in real-time. The path-planning module [25] is applied for obstacle avoidance when the virtual human walks to a specific location using the walk engine [26]. An XML file is automatically created with all the obstacles coordinates from the virtual environment in 3DSmax [27]. Finally its 3D viewer shows, in real-time, what the virtual human decides to do at each moment in time.

Users had to define rules in order to create internal variables, motivations, goal-oriented behaviors or actions in a parameterization file. One rule is necessary for each new element defining all the element parameters (around twenty different in total). For example, you can specify the name for each element, indicate thresholds of the subjective evaluation in internal variable rules, the factors of the perceptions and the motivation goals in behavior rules or keyframes and perception in actions rules... For this test, 67 rules are required but new elements can

be defined. The parameters can be change before and during the simulation. Internal variables and their action effect factors are generated at random within a certain range to be standardized. During the simulation, you can change almost all existing parameters and in particular each action effect factors increasing or decreasing internal variables (see figure 15 in the color plate). Then you can define a personality for the virtual human such as lazy, greedy, sporty, tidy, dirty... Moreover scripted behaviors and many parameters such as 3D viewer options are available thanks the python script module.

The number of motivations is not limited in the motivational model of action selection. The limitations reside in the complexity of animations. That's why we use keyframes for each action interacting with objects, designed in 3Dmax [27] with inverse kinematics scripts. The keyframes need to be divided into three parts: one for preparing the action, one for the action itself and one for terminating it. In this case, the action keyframe can be interrupt easily. The satisfaction of the motivation begins only during the second part decreasing the internal variables. When a long action is executed, the simulation can be accelerated with the graphical interface or automatically, such as sleeping or reading. Keyframes can be added at the beginning and goals where the virtual human will do them are automatically detected and added in the simulation.

## 5 RESULTS

Results show that our motivational model of action selection is enough flexible and robust for designing motivationally autonomous virtual humans in real-time. The following screenshots of the graphic interface are showing the evolution of the internal variables, motivations and actions during the simulation. It is only for clarity purposes that sometimes results are based on two motivations.

### 5.1 Flexible and reactive architecture

#### 5.1.1 Opportunist behaviors and interruptions

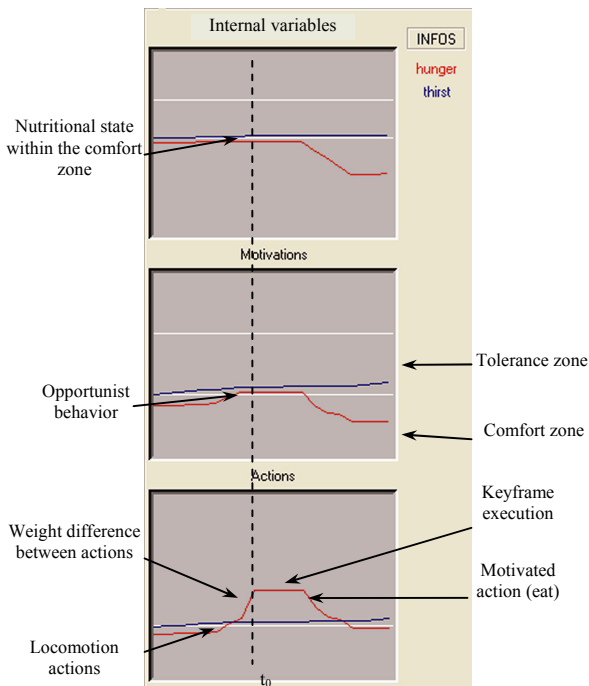


Figure 8. Opportunist behaviors.

In the figure 8, the virtual human is thirsty and goes to a drink location. He doesn't take hunger into account because the corresponding nutritional state is within the comfort zone. However, when the virtual human passes near food, an opportunist behavior occurs, generated by his perception system. Hunger is therefore increased proportionally to the distance to the food source and exceeds the tolerance threshold ( $t_0$ ). As the corresponding goal-oriented behavior is also increased, the eat action becomes the most activated one and is then chosen by the action selection model, even if the nutritional state is within the comfort zone and the hunger is not the highest motivation.

#### 5.1.2 Compromise behaviors

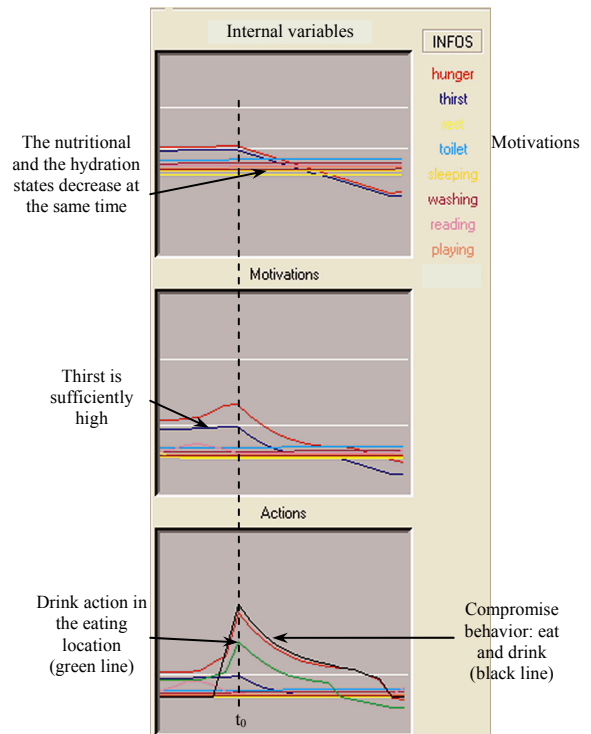


Figure 9. Compromise behaviors.

In this example (figure 9), the highest motivation is hunger and the virtual human should go to a known food place where he can satisfy his hunger. However, at another location, he has the possibility to both drink and eat. As thirst is sufficiently high, he decides to go to this location even if it is more remote, where a compromise behavior can satisfy both nutritional and hydration states at the same time ( $t_0$ ), instead of going first to the eating place and then to the water source. As long as both the nutritional and hydration states have not returned within their comfort zones, the compromise behavior continues.

### 5.2 Robust and goal-oriented architecture

#### 5.2.1 Coherence

When the nutritional state enters the tolerance zone ( $t_0$ ), the virtual human begins to take hunger into account, thanks to a "subjective" evaluation of the motivation. Then behavioral sequences of intermediate actions are generated ( $t_0-t_1$ ), in order to satisfy hunger. Finally the eat action is performed ( $t_1$ ) and the nutritional state decreases accordingly, until it is back within the

comfort zone ( $t_2$ ), whereas hunger is maintained as the highest motivation.

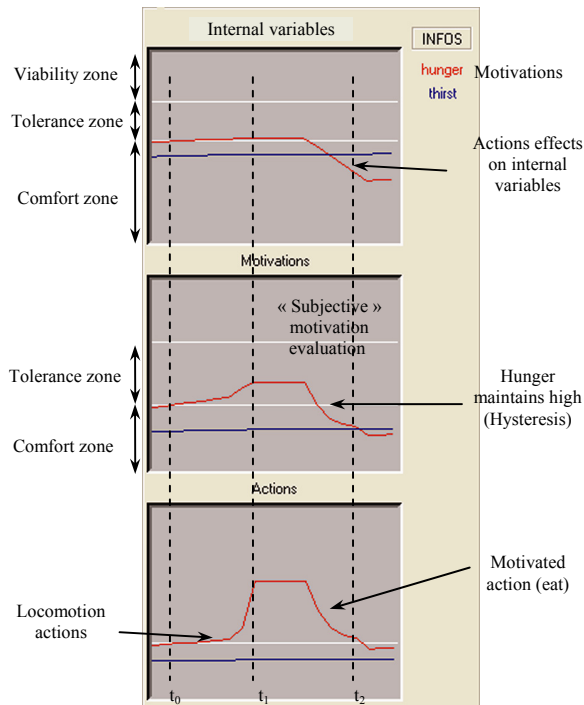


Figure 10. The influence of the motivation in the action selection mechanism.

### 5.2.2 Persistence

During 32000 iterations, internal variables are maintained within the comfort zone with an average of 80 percent (see figure 11). Any internal variables are reached the danger zone. The percentage of presence in the tolerance zone correspond to the time that the virtual human had focused his attention to reduce the corresponding internal variables. The differences of presence depends on the action effect factors which increase or decrease more or less rapidly internal variables and if the associated motivation could be satisfy by compromise actions. In this case, the threshold for the comfort zone is reduced to prefer the compromise behaviors. Moreover the perceptions can also modify the values of the activities at the level of motivations and goal-oriented behaviors.

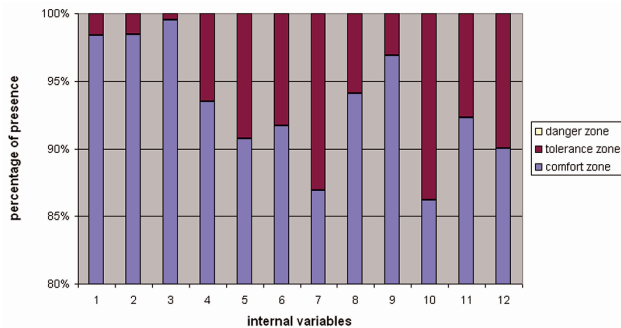


Figure 11. The percentage of presence for the twelve internal variables (see table 2) according to the threshold system (comfort, Tolerance and danger zone) over 32000 iterations

It shows that our action selection model has a good persistence of actions due to the subjective evaluation of the motivations, the hysteresis, the perception system and the weight of the action rules. Indeed the subjective evaluation allows to adapt the length of the motivated actions compared to the urgency of the motivations. The hysteresis maintains the motivation values high even if the respecting internal variable values decrease (see figure 10). The perception system increases the values at the level of motivations and goal-oriented behaviors when the virtual human is near goals where he could satisfy some motivations. The motivated actions rule weights are twice as much as that of the intermediate ones in order to prefer motivated actions over intermediate ones. It takes part in the persistence of actions increasing the values of possible motivated actions. The weight difference is responsible for the sudden increase of the value in the figure 10. Without this difference of weight the persistence of actions is reduced and the risks of dithering increase. In the end when the virtual human begins to drink for example, the more the eat action is high, the more the hunger motivation will take time to decrease and the more the nutritional state will decrease proportionally.

### 5.2.3 Time-sharing

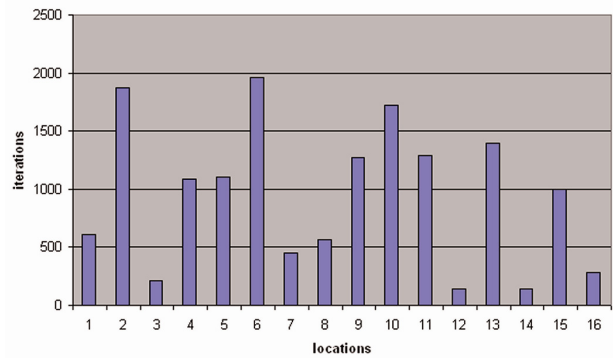


Figure 12. Time-sharing for the sixteen goals (see table 2) over 32000 iterations

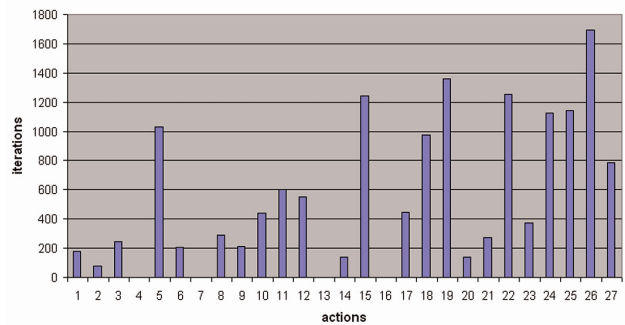


Figure 13. Time-sharing for the twenty seven actions (see table 2) over 32000 iterations

During the 32000 iterations, the model has a good control of the temporal aspects of behaviors. The virtual human has well sharing his time between conflicting goals. He has gone at the sixteen goals (see figure 12 and table 2) even if he could satisfy same motivations at several goals. For example 12, 13, 14 and 15 correspond to several goals where he can do push-up. The perceptions and the distance to reach goals help the architecture to decide. The time that the virtual human really spend there depends mostly on the frequency of the action effect factors on internal variables and if goals handle compromise actions. In this

case, the virtual human has a tendency to go often to these goals (1, 2, 4, 5, 6 and 11) to satisfy several motivations at the same time. However the virtual human don't do all possible actions (see figure 13). Indeed when compromise actions are available: eat and drink, separated actions can also be done: eat or drink, at the same location. As the compromise actions (23, 24, 25, 26 and 27) are often chosen as defined in the model, the corresponding separated actions in these goals are neglected (2, 4, 7, 11, 13 and 16). Moreover they are generally farther than the other actions from the default location where the virtual human often is, except the cook1 action (11) almost closer than the cook action.

## 6 CONCLUDING REMARKS AND FUTUR WORKS

The results demonstrate that the model is flexible and robust enough for modeling motivational autonomous virtual humans in real-time. The architecture generates reactive as well as goal-oriented behaviors dynamically. Its decision-making is effective and consistent and the most appropriate action is chosen at each moment in time with respect to many conflicting motivations and environment perceptions. The persistence of actions and the control the temporal aspects of behaviors are good. Furthermore, the number of motivations in the model is not limited and can easily be extended. In the end, the virtual human has a high level of autonomy and lives his own life in his apartment. Applied to computer games, the non-player characters can be more autonomous and believable when they don't interact with users or execute specific tasks necessary for the game scenario.

Actually we are testing to associate our model with a collaborative behavioral planner in a multi-agents environment developed in our lab. The continuation of this work is to add an emotional level [23, 28] and social capabilities [29, 30] in order to increase the autonomy of virtual humans. The emotions will give richer individualities and personalities. Social capabilities will help virtual humans to collaborate to satisfy common goals.

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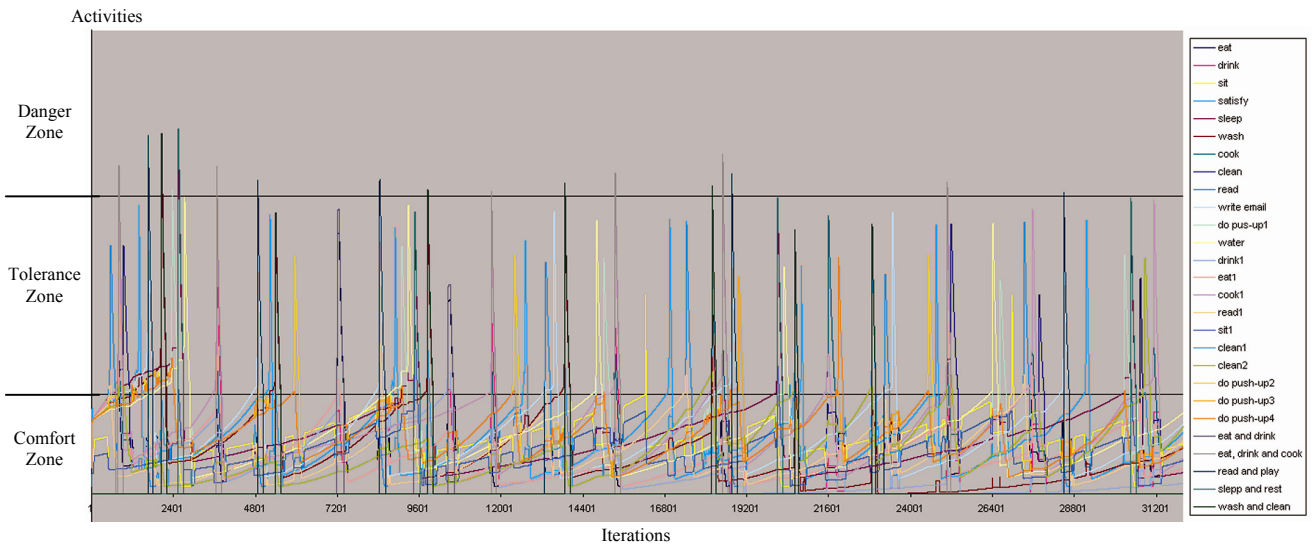


Figure 14. Evolution of the 27 action activities in real-time during 32000 iterations. The actions zones are adapted from the zones for internal variables. Most of the time, the actions are within the comfort zone.

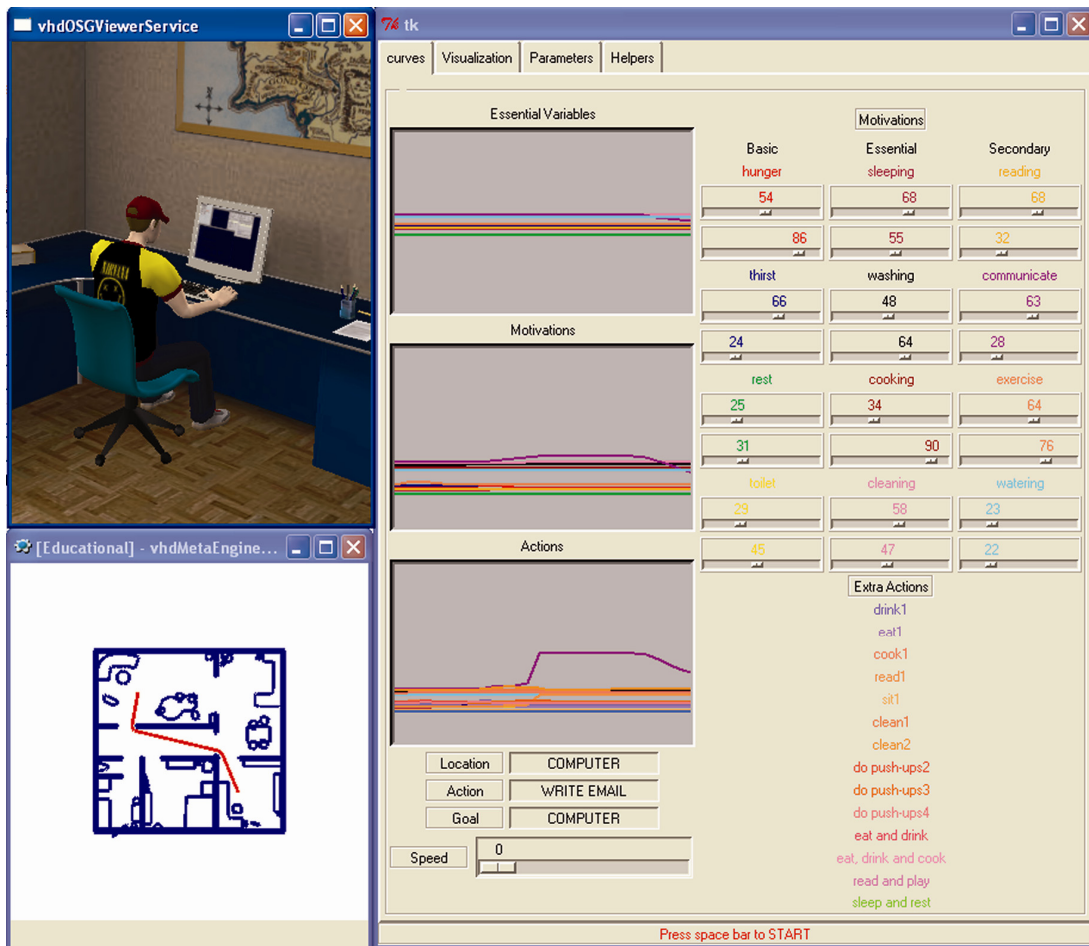


Figure 15. Overview of the application with the 3D viewer, the path-planning module and the graphic interface. Action effects can be changed and the evolution of model levels monitored in real-time