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Action Learning for Autonomous Virtual Actors

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Abstract— **The goal of our work is to model believable virtual actors. Within the framework of learning by imitation, the virtual actor must be able to modify its prototypic behavior for miming in its imaginary world the observed behavior of a model which can be another virtual actor or an avatar controlled by a human operator. Each virtual actor has sensors for perceiving and effectors for acting and also a library of prototypic behaviors specified by FCMs for simulating it-self and others in its imaginary space. FCMs can give true perception & emotion. We propose a FCM-learning algorithm using meta-knowledge about learning in order to imitate a given behavior in real-time. The virtual actor autonomously selects training periods. This selection is inspired by neurophysiological experiments about active perception and hippocampus. The implementations undertaken in the multi-agent environment *oRis* are related to a sheepdog gathering sheep and to the adaptation of a virtual sailor to a given sailing ship.**

Keywords— **Active Perception, Autonoy, Believable Agent, Fuzzy Cognitive Map, Imitation**

I. Introduction

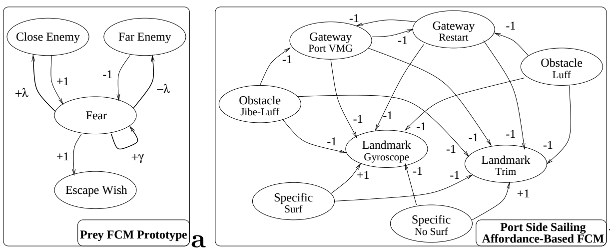
Virtual worlds are peopled with autonomous entities improvising in free interaction [Hayes-Roth 96]. The goal of our work is to model believable virtual actors [Bates 92]. Autonomous entity is one of the keys for believable virtual human creation [Thalmann 00]. A virtual actor is an autonomous agent (or animat [Meyer 91]) having its own culture, personality, emotions. Our virtual actors have sensors for perceiving, effectors for acting and also a library of prototypic behaviors specified by Fuzzy Cognitive Maps (FCMs) [Parenthoën 01]. Behavioral control of intelligent characters needs explicit knowledge [Granieri 95], [Funge 99]. FCMs contain not only declarative but also explicit knowledge. An expert in collabaration with an ergonomicist can provide the prototypes of such FCMs [Parenthoën 02]. Connection between the autonomous agent and FCM results by fuzzyfication of sensors which determines the extern activations of the perceptive concepts in this FCM, while defuzzyfication of internal activations of motor concept fixes effectors. Internal concepts can translate emotions and are used for FCM dynamics calculus. FCM models perception (*versus* pure sensation) thanks to links fromwards internal towards perceptive concepts. A virtual actor has also an imaginary world, in which it can simulate its own behavior but also prototypic behavior of other actors. It can use this imaginary space to choose appropriate strategy between possible ones, not by logically reasoning but by simulating its behavioral model [Maffre 01]. As underlined A.C. Schultz 8 years ago, learning initially takes place under simulation [Schultz 96]. Within the framework of learning by imitation [Gallese 00], [Mataric 01], the virtual actor must be able to modify its prototypic behavior for miming in its imaginary world the observed behavior of a model which can be another virtual actor or an avatar controlled by a human operator. As our agent uses FCMs for specifying prototypic perceptive behaviors, we propose an algorithm for learning the weights of the causal links between concepts in a prototypic FCM in order to imitate a given behavior, without modifying neither the FCM influence graph structure, neither the sensor fuzzyfication, nor the motor concept defuzzyfication. This modification of causal links between concepts uses meta-knowledge about learning.

Our virtual actor autonomously selects training periods using active perception [Berthoz 97]. The "perception as anticipation"-approach fuses perception-decision-action cycle into one consistant neurophysiological process. Researchers in neuroinformatics have developped such artificial neural process applied to animats [Heinze 01]. Neurophysiologists have demonstrated the importance of hippocampus in prediction of trajectories [Buzsaki 92], [Lisman 95] and recently the hippocampal structure has inspired cybernetics: hippocampus is used to learn, store and predict transitions between multimodal states, furthermore it is not also crucial for novelty detection but it also merges explicit planning and sensorimotor functions in a single and coherent system [Gaussier 02], [Trullier 00].

Next section explains how a virtual actor can adapt prototypic behavior in its imaginary world in real time to imitate observed behavior. It describes FCM learning algorithm, studies its complexity and its convergence. An application implemented in the multi-agent environment *oRis* [Harrouet 00] deals with sheepdog gathering sheep. Section III proposes active perception as a basis for autonomous action learning and an implementation relating to the adaptation of a prototypic virtual sailor to a given sailing ship.

II. Learning per Imitation

This section presents learning algorithm for virtual FCM-controlled actors. We will describe a method allowing an adaptation per imitation in real-time. The actor observes the model and simulates the behavior of an image-actor having to follow this model. This image can be its own image, or the one of another actor simulated by prototypic FCMs from its library. The virtual actor endeavours to imitate in its imaginary world the behavior of a model by adapting its FCMs. This model can be an autonomous virtual actor or an avatar controlled by a human operator. The imitator has only access to a model sensor/effector estimation by observation. The imitator must have it-self sensors allowing this estimate. It makes the assumption that the behavior of the model is controllable by a one of its modified prototypic FCMs from its library. Figure 1 show two examples of such prototypes: one for a virtual sheepdog imagining prey, the other for a virtual helmsman selecting affordances. It has then to identify model character by modifying the image FCM link matrix.



These FCMs resuming expert's knowledge are prototypes. A sheepdog uses the FCM in (**a**) while gathering, for imagining sheep behavior then adopting a suitable stategy. It is a not only sensitive but perceptive FCM, thanks to links (bold) from internal concept *fear* towards perceptive concepts: a high γ (resp. λ) gives a stressed (resp. paranoiac) sheep. The FCM in (**b**) drives the virtual helmsman's modality of action. It is used by the virtual helmsman during sailing for selecting affordance among possible ones.

Fig. 1. Prototypic FCMs for Virtual Actors

An adaptive FCM must modify the weights of causal links between its concepts according to gathered data from the external world, so that its dynamics generate the desired behavior. Kosko has proposed two different Hebb type methods [Hebb 49] for an expert given limit cycle learning by FCM [Kosko 88]. One is based on the correlations between activations [Kosko 92], the other on a correlation of their variations (differential hebbian learning) [Dickerson 94]. The advantage of differential learning is that higher order causal relations can be learned if it correlates multiple cause changes with effect changes. Kosko's differential hebbian learning algorithm on the one hand is based on the knowledge of a limit cycle including all the concepts and provided by an expert, on the other hand makes the assumption that external forced activations are constant. However external activations evolve in time and we can not have such a limit cycle, because only estimated model sensors and effectors can be observed: a FCM having generated them is not available; a human operator can lead this model. The actor will simulate an image of model behavior in its imaginary space with an adaptive FCM, and will compare the image-effector with the model-effector estimation to update this FCM. In this section, it is the model which decides the training period, but we'll see in the next section how to autonomize the learning period choise using hippocampal inspiration. At the end of the training period, the FCM adapted to the model imitation replaces the initial prototype.

The algorithm of adaptation that we propose is an iterative cycle in four stages between t and $t+1$:

1. estimation of model-sensors and model-effectors are measured,
2. sensor are fuzzyfied into perceptive concept external activations, calculation of the FCM dynamics uses equation (1) with N equals the lenght of the longest acyclic path added to the length of the longest cycle in the influence graph, then image-effectors are obtained by motor concept internal activation defuzzyfication,
3. comparison between image-effectors and model-effectors is performed, and formula (2) generates a set of desired pseudo-activations by going up the influence graph from motor concepts towards perceptive concepts without modifying links and by using meta-knowledge about learning,
4. FCM causal links are updated by applying discret differential hebbian learning to the sequence corresponding to the passage from FCM activations towards desired pseudo-activations, according to learning law (3).

The **first** stage consists in observation: imitator measures features about the model, which are necessary for model-sensor and model-effector estimations. We make the assumption that these features are available for the imitator.
The **second** stage corresponds simply to the usual use of a FCM for the control of a virtual actor, and determines image-actor FCM activations at moment $t + \delta t \approx t$ in the imaginary world, according to model-sensor estimation and FCM dynamics with N itera-

tions:

$$a(t+\tfrac{I}{N}\delta t) = S(G\left(f(t), L^T \cdot a(t+\tfrac{I-1}{N}\delta t)\right)) \quad \text{for } I = 1, \cdots, N \ ; \quad \delta t << 1 \tag{1}$$

n being FCM concept number, $f=(f_i)_{i\in[\![1,n]\!]}$ external activations coming from sensor fuzzyfication, $a=(a_i)_{i\in[\![1,n]\!]}$ internal activations, $L=(L_{ij})_{(i,j)\in[\![1,n]\!]^2}$ link matrix, $G:(I\!R^2)^n \rightarrow I\!R^n$ a comparison operator and S a standardization function transforming each coordonate by the sigmoidal function: $\sigma(x)=\frac{1+\delta}{1+e^{-\rho(x-a_0)}}-\delta$, with parameters $(\delta,\rho,a_0) \in \{0,1\} \times I\!R_*^+ \times I\!R$. FCM motor concept defuzzyfication at moment $t+\delta t \approx t$ provides image-effectors. For more clearness, we note a the resulting internal activations $a(t+\delta t)$ in next paragraphs.

The **third** stage recursivly generates sets of pseudo-activations $(P_i)_{i\in[\![1,n]\!]}$ translating an orientation for FCM dynamics. The principle consists in going up the influence graph from motor concepts towards perceptive concepts proposing pseudo-activation values according to meta-knowledge about learning and bringing image-effectors closer to model-effectors estimation. Let's detail the recursive proccess:

Initialisation $m=0$: entering into the FCM from effectors. A set I_0 represents indices of concepts defuzzyfied onto image-effectors. For each $i \in I_0$, we apply the decision learning meta-knowledge: two potential pseudo-activations $p_i^{\pm}=\sigma(a_0 \pm \frac{\alpha_i}{2\rho})$ simulate an active/inactive concept C_i, $\alpha_i \geq 1$ translating choise radicality. With the a_i value, that makes 3 possible pseudo-activations $p_i=a_i$, p_i^+ or p_i^- for each C_i. The $3^{\text{Card}I_0}$ combinations are defuzzyfied, compared to model-effector estimation and the best combination $(p_i^{0,\{\}})_{i\in I_0}$ is kept (the 0 deals with defuzzyfication and the $\{\}$ is a set of futur labels). $\forall i \in I_0$, $P_i=\{p_i^{0,\{\}}\}$. The others pseudo-activations sets $(P_i)_{i\in([\![1,n]\!]\setminus I_0)}$ are empty.

Progression from m to $m+1$: Let $I_m \subset [\![1,n]\!]$ be the indice set of concepts which desired pseudo-activation set is not empty. For $i \in I_m$, note a_i (reps. f_i) internal (resp. extern) activation of concept C_i, $P_i=\{p_i^{k_1,\{\cdots\}},\cdots,p_i^{k_L,\{\cdots\}}\}$ its desired pseudo-activation set which cardinal equals L and $J \subset [\![1,n]\!]$ the indice set of concepts which are causes for the concept C_i (*i.e.*:$L_{ji}\neq 0$) and such that the arc from C_j to C_i has not been studied: $\forall\lambda \in [\![1,L]\!]$, $j \neq k_\lambda$. We will calculate pseudo-activations P_j for $j \in J$ as follows:

- For each $j \in J$, we apply the decision learning meta-knowledge: two potential pseudo-activations p_j^+ and p_j^- are calculated (2) so that their influence on a_i causes a clear choise between an active C_i or an inactive C_i, taking into account extern activations, with $\alpha \geq 1$ translating the choice radicality:

$$p_j^{\pm} = \left(a_0 \pm \frac{\alpha}{2\rho} - f_i - \sum_{l\neq j} L_{li}a_l\right)/L_{ji} \tag{2}$$

- Then we select randomly a $\lambda \in [\![1,L]\!]$. That gives a $p_i^{k_\lambda,\{\cdots\}} \in P_i$ and we choose among the $3^{\text{Card}J}$ possible combinations $p_j^i=a_j$, p_j^+ or p_j^- for $j\in J$, the one $p_j^{i,\{\cdots,k_\lambda\}}$ which gives a C_i activation $\sigma\left(G_i(f_i,\sum_j L_{ji}p_j^i)\right)$ the nearest to $p_i^{k_\lambda,\{\cdots\}}$,
- Thus we obtain a new set of concept indices with a not empty desired pseudo-activation set: $I_{m+1}=I_m \cup J$ with $P_j=P_j\cup\{p_j^{i,\{\cdots,k_\lambda\}}\}$for $j \in J$.

Termination: if for each $i \in I_m$, the corresponding J set is empty, every arc belonging to paths going into $(C_i)_{i\in I_0}$ has been studied.

The **forth & last** stage modifies FCM link weights, in order to direct its dynamics towards a behavior approaching the model. Contrary to Kosko who uses a cycling cycle and a learning rate decreasing with time (see [Dickerson 94] page 186), we make only one stage from intenal activations a to link corresponding desired pseudo-activations p for the weight modification without cycling and preserve a constant learning rate $r(t)=R$, in order to ensure a strong adaptivity for our virtual actor. Formally, noting $\mathcal{A}\subset[\![1,n]\!]^2$ the arc set of the FCM, $\beta \in]0;1+\delta[$ a sensitivity level and $s: I\!R \rightarrow \{-1,0,1\}$ the discrete function $s(x)=-1,\ 0$ or 1 respectivly if respectivly $x \leq -\beta$, $-\beta < x < \beta$ or $x \geq \beta$, the learning algorithm follows the equations:

$$\begin{array}{l}
\forall(i,j)\in\mathcal{A},\ \text{if } \exists k \in [\![0,n]\!],\ p_j^{k,\{\cdots,i,\cdots\}} \in P_j, \\
\text{we take such a } k \text{ and :} \\
\begin{cases}
\Delta_i = s(p_i^{j,\{\cdots\}}-a_i),\ \Delta_j = s(p_j^{k,\{\cdots,i,\cdots\}}-a_j) \\
L_{ij\,(t+1)} = \left| \begin{array}{ll} L_{ij\,(t)} + R(\Delta_i\Delta_j - L_{ij\,(t)}) & ,\ \text{if} \quad \Delta_i \neq 0 \\ L_{ij\,(t)} & ,\ \text{if} \quad \Delta_i = 0 \end{array} \right.
\end{cases} \\
\text{else } \mathcal{A}_{ij} \not\in \{\text{path to effectors}\}:\ L_{ij\,(t+1)} = L_{ij\,(t)}
\end{array} \tag{3}$$

We also keep some link weights inside given bondaries $\mathcal{B}_{ij}=[L_{ij}^{min},L_{ij}^{max}]$ so that the adapted behavior remains believable according to the expert: if $L_{ij\,(t+1)} < L_{ij}^{min}$ then $L_{ij\,(t+1)}=L_{ij}^{min}$ and if $L_{ij\,(t+1)} > L_{ij}^{max}$ then $L_{ij\,(t+1)}=L_{ij}^{max}$. This allows imitation while preserving imitator's personality and emotions.

We have implemented this algorithm in the multiagent environment *oRis* [Harrouet 00] applied to sheepdogs gathering sheep. A dog simulates herding in its imaginary space using for example two viewing strategies: one associated to vision restricted to a closed neighborhood (dog only takes care about sheep acting in a ten meters raduis circle), the other to the largest vision possible (dog takes care about every sheep). The results of these simulations are compared in term of best gathering, then the dog adopts the more suitable stategy to gather sheep. If the herd is divided into two distant groups for example, dog adopts after a simulation in its imaginary world the restricted vision strategy to prevent it to run unefficiently between the two groups. For accuracy in the imaginary world, our virtual sheepdog has to identify its prey prototype shown in figure 1**a** to a given sheep character. It can also have to learn a way of gathering by the imitation of a shepherd-controlled model or another dog, then the prototypic FCM used in its imaginary world is its own FCM.

In practice, the experiments undertaken on sheepdog show that convergence occurs and that the sheepdog is able to adapt its prototypic FCMs to specific sheep and dogs. We could modify the learning rate through time, as a decreasing sequence tending towards zero and with a diverging to infinity associated series. That would ensure a theoretical FCM weight convergence, but the adaptivity would be less and less strong with the age of the actor.

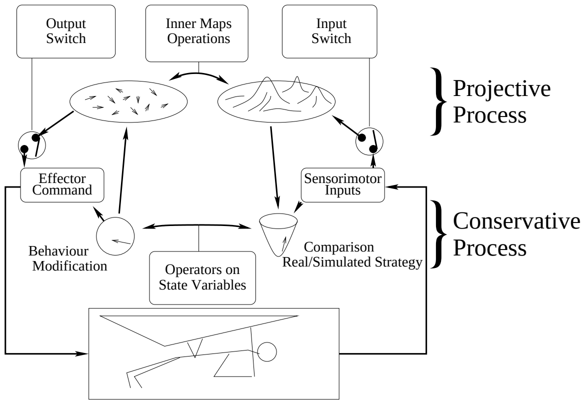
The complexity of this algorithm is a polynomial function of the number n of concepts given by the expert, and even a $\mathcal{O}(n)$. Without paying attention, one could believe that this algorithm has an exponential complexity but it hasn't. Indeed, for an expert, the causes of a concept are always in a very limited number (seldom more than five), therefore the number of arcs arriving on each concept is rised by M ($M \approx 5$), *ie:* $\mathrm{Card}J \leq M$. $3^{\mathrm{Card}J}$ is thus raised in practice, whatever the number of concepts implied in the FCM. The same applies to the calculation of FCM dynamics which complexity is a $\mathcal{O}(n)$ whereas could seem to be a $\mathcal{O}(n^2)$, thanks to the great number of zeros in the link matrix; the number of not null links in a column being no more than M, whatever could be n. This algorithm can thus be implemented for a use in real time.

III. Action Learning

We include the previous algorithm in an active perception structure, enabling a virtual actor to choose alone the learning periods, while imitating a human operator performing an action. Then we briefly present action learning applied to the implementation of virtual sailor.

A. Active Perception for Action Learning

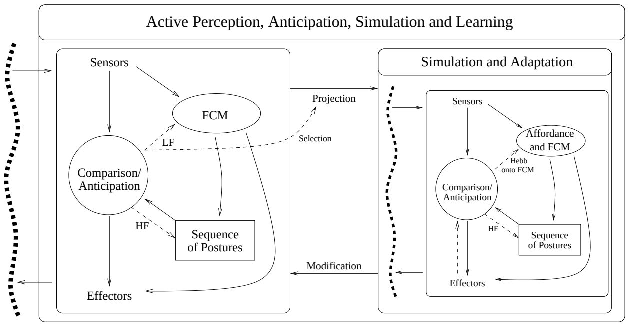
Brain can be considered as a biological simulator which predicts using its memory and making hypothesis about inner modeling of the phenomenon. Let's take a sportman as an example: he will mentally and predictivly go though the evens of the performance in the same time he will performe it, and sporadically verify his sensors' states. The inner simulation of movement is made easier by a neuronal mecanism of inhibition. Brain possesses a biological modeling of the action to be performed. It does not only compare sensorial with memorised informations, it also uses anticipatory mecanisms (figure 2 [Droulez 88]).



During an action, the brain uses two modalities in parallel. A predictive or projective one for selecting sporadicaly the state of some sensorimotor sensors. And a reactive or concervative one for holding some variables in boxes defined by action intentions. The brain would lost too much time in controlling every time all the sensors.

Fig. 2. The two Modalities of Movement Control by Brain

Let's take an agent which behavior is specified by an affordance-based FCM [Morineau 01]. Each affordance belonging to this FCM is associated with a specific strategy of trajectory, described by a sequence of sensorimotor configurations. An expert gives these caracteristic sensorimotor configurations associated to each affordance. If affordance selection is correct, then the prototypic sequence of sensorimotor configurations should be observed. The simulation of behavior in imaginary space is synchronized with the real time behavior of the virtual actor. This synchronization follows neurophysiological experiments on hippocampus in wich were observed oscillations permitting prediction of trajectories [Buzsaki 92], [Lisman 95]. A low frequency oscillation ask the context of the action to the FCM. During one of this cycle, a high frequency oscillation synchronizes the prototypic sensorimotor configurations with the real time observations by pattern matching. This pattern matching between configurations and observations is only done on the prototypes associated with the affordance selected by the FCM. The frequency ratio of these oscillations is equal or greater than the number of configurations in this prototypic sequence. The virtual agent then go through the sequence of configurations discribing the contextual strategy, always anticipating to reach the next configuration. If the pattern matching fails on every configurations, then a new context is asked to the FCM, inhibitting the current selected affordance and memorizing sensorimotor features of the last low frequency cycle. The agent will virtualy run in its imaginary space these stored sensorimotor features for various affordances. Then the agent chooses the one which best fits this low frequence cycle sensorimotor features according to the predicted prototypic sequence. This choise permits an hebbian modification of the FCM weigths, exciting the chosed affordance and inhibiting the others.



Simulation in the simulation: the active perception structure for autonomous virtual actors. The FCM selects an affordance. Then a strategy is starting, consisting in a sequence of postures characterized by sensorimotor configurations. The expected configurations are compared to sensors, then synchronyze the HF sequence when recognition occurs. If recognition fails, that puts in phase the LF oscillation of the FCM and projets onto simulation mode the last LF cycle having led to anticipation mistake. This recorded cycle is played in a imaginary space, forcing affordances to choose the most adapted one, then modifies FCM links by hebbian learning.

Fig. 3. Active Perception: a Key for Autonomous Learning

B. Virtual Believable Helmsman

Within the framework of the realization of a virtual sailing ship intended for sporting drive, it is significant to give believable behavior to virtual sailors. Such virtual sailors have to be able to act, within a virtual marine universe, as a helmsman could pilot, as a reglor could play on the veils and as a tactician could choose strategies of navigation. The behavior of the sailing ship must be qualitatively compatible with anticipations of a real sailor. For that, it is necessary to understand the affordances which a sailor uses to locate himselve on the waves and to choose a trajectory. Indeed, the more the extraction of affordances is pertinent, the more believable will be the virtual sailing ship thus prototyped. We have discribed a virtual believable helmsman using affordance-based FCMs and active perception in [Parenthoën 02]. It uses virtual sensors about sailing boat features and virtual effector to steer the helm. But its behavior is prototypic and we would like such a virtual sailor be able to adapt it-self to different sorts of sailing boats, by imitating a human helmsman.

We ask to the virtual helmsman to learn affordance selection by modifying its affordance-based FCM of the figure 1**b**. The FCM activation by fuzzyfication of sensors determines affordance choise *via* FCM dynamics following a low frequency oscillation. The virtual helmsman then uses this selected affordance to adopt a suitable strategy. A strategy is specified by both an expected sequence of postures caracterised by some sensorimotor features and a parametrisation of a reactive process associated to each posture. The reactive process uses the equation (4) parametrized by a 5^{uplet}, $(\mu_{\text{c}}, \mu_{\text{t}}, \mu_{\text{r}}, \mu_{\delta\text{r}}, \mu_{\delta\text{c}}) \in \mathbb{R}^5$ associated with each no specific affordance. This formula results from physical study. It is based on the piloting description as a compensation by the rudder blade effect of the various couples unbalancing a sailing ship around the vertical axis.

$$v^2_{\text{boat}}\theta_{\text{helm}} = \left| \begin{array}{c} \mu_{\text{c}}\Delta_{\text{compass}} + \mu_{\text{t}}\Delta_{\text{trim}} + \\ \mu_{\text{r}}\theta_{\text{roll}} + \mu_{\delta\text{r}}\delta\theta_{\text{roll}} + \mu_{\delta\text{c}}\delta\theta_{\text{compass}} \end{array}\right. \qquad (4)$$

Reactive formula (4) identification is performed by mean least square (MLS) on an affordance-based partition accorging to affordance selection. The navigation strategy is chosed when the oscillation begins. If the frequency is too low, the context could change before the end of the oscillation. If this is not detected, the behavior could be dramatic. If the frequency is too high, calculus load increases and adaptations to each new context will provoque a lack of believability: too much energy consuming from a human point of view. Furthermore, the highest is this frequency, the lowest time remains for the learning process. Even if frequency is low, the virtual helmsman should be able to synchronize its low frequency oscillation with pertinent perception of the environment. Each affordance is also associated with a specific strategy of trajectory, described by a sequence of sensorimotor configurations. An expert gives these caracteristic sensorimotor configurations. As an example, we detail such a sequence of configurations (here 3 postures) associated with the restart affordance:

1. Posture $(\theta 1_{\text{helm}}, \Delta 1_{\text{compass}}, \Delta 1_{\text{trim}})$. Calculate only once $\theta 1_{\text{helm}}$ using the reactive process (4) with restart coefficients and $(\Delta 1_{\text{compass}} = \Delta_{\text{compass}} - 5^o, \Delta 1_{\text{trim}} = \Delta_{\text{trim}} + 10^o)$. Inibit the reactive processus and observe compass trim and lodging variations: when $\theta_{\text{helm}} = \theta 1_{\text{helm}}$, should be observed $dh < 0$, $dc > 0$ (else should have been selected jibe-luff affordance) and dr under mean + standard deviation (else should have been selected luff affordance).
2. Posture $(\Delta 2_{\text{compass,trim}} = \Delta 1_{\text{compass,trim}}, v2_{\text{boat}})$. Use unhibited reactive process (4) with $\Delta 2_{\text{compass,trim}}$ for calculating θ_{helm} dynamically. Observe only the speed v_{boat}. It should increase greater or equal to $v2_{\text{boat}}$. If not increasing ask a new low frequence oscillation affordance selection.
3. Final Posture $(v_{\text{boat}} \geq v2_{\text{boat}})$: use then the usual unhibited reactive process (4) with the restart coefficients and ask a new low frequence oscillation affordance selection.

If the first configuration leads to mistake, then the last low cycle of sensorimotor features is memorized and the agent virtualy runs in its imaginary space this cycle for various affordances and chooses the one with lowest mistake for the first posture (characteristic of strategy). This choise gives desired affordance values in the FCM and permits link modification following hebbian principle discribed in precious section. By this way, our autonomous virtual actor learns how to manage affordance selection on this specific sailing boat.

IV. Conclusions and Futur Work

We use FCMs to control virtual entities behavior because FCMs contain explicit knowledge and can give true perception and emotions. We have described a FCM-learning algorithm included in an active perception process which gives autonomy for training period choise. The implemented FCM-learning algorithm and active perception give imitation ability in real time to our virtual actors. This imitation is based on prototypic behaviors owned by the virtual entity and constituing its fixed "culture". This allows our actors to imagine more accuratly the consequenses of their actions while cooperating with other entities, then to choise suitable strategy of action. A part of meta-knowledge used for learning depends on expert description during prototypic FCM elaboration and allows imitation while preserving imitator's personality & emotions. Although, neither the prototypic fuzzification of sensors, nor the prototypic defuzzyfications onto effectors are modified. Further work will try to find an autonomous process tuning these fuzzy transformations. Furthermore, if virtual helmsman is believable in a virtual world, why not to make its steer a real sailing boat.

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